INTEGRATING PLUG-IN HYBRID ELECTRIC VEHICLES AND VEHICLE-TO-GRID TECHNOLOGY INTO THE NEW YORK ELECTRICITY MARKET

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Corey David White

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ABSTRACT

The introduction of plug-in hybrid electric vehicles (PHEVs) into the transportation system will provide both opportunities and challenges for those who own the vehicles and power systems operators.

The opportunities come in the form of the ability to provide vehicle-to-grid (V2G) services including peak load reduction and frequency regulation. Utilizing these services can provide profits for the vehicle owners, cost savings for the grid operators, and reduced air pollution. The primary goal of this study is to analyze these benefits from the viewpoint of the individual vehicle owner. It is found that there is little financial incentive when V2G services are used for peak reduction. There is much greater potential for financial return when V2G services are used to provide frequency regulation, likely enough to incentivize many people to participate in such a program. Proposed in this paper is a system that combines these V2G services into a single program, which could have the effect of ensuring profits for the individual, while still providing cost-saving opportunities for grid operators, and emission reductions during the times when it is needed most.

In addition to the opportunities brought about by increased penetration of PHEVs, there are challenges as well. This comes mainly in the form of increased demand for electricity. The possible effects on electricity load of increased PHEV penetration and V2G participation are analyzed in this paper. Furthermore, an econometric model is used to predict the effect of increased electricity load on electricity price at each hour of the day. It is found that increased PHEV penetration can (in a regulated charging scheme) increase electricity loads and prices during the hours when electricity loads and prices are currently lowest. Furthermore, if V2G technology is used for peak reduction, electricity loads and prices can be reduced

during peak electricity demand hours. The overall effect of this is a flattening of the daily electricity load and price profiles, which is likely to be beneficial for power system operators. The flattening of the daily electricity price profile has the effect of reducing profits when V2G technology is used for peak reduction because it raises the price during charging (buying electricity) and lowers the price during discharging (selling electricity).

While the analysis presented here works within the framework of the current electricity markets, it is possible that the best use for V2G technology could come in a program that allows grid operators to dispatch the stored energy for the optimal purpose (e.g.: peak reduction, regulation, reserves, ramping) at any period of time. This would require a different type of market structure, possibly even a separate market for storage, in which V2G services could participate.

BIOGRAPHICAL SKETCH

Corey was born in Berkeley, California and spent most of his youth in the nearby town of Lafayette. His interest in environmental matters began in high school, and then continued into college where he chose his major of Environmental Economics. Becoming more of a pragmatic environmentalist than anything, he began becoming most interested in ways to actually improve the environment instead of studying the problems themselves. This is where his interest in energy began, and all of his undergraduate research was focused on topics related to energy. Corey graduated from California State University, Chico with his degree in Environmental Economics and soon after found his way to Cornell University to study Applied Economics and Management. Upon arriving at Cornell, Corey quickly got involved with the Energy and Environment Research Lab, where he began the research that has culminated in his thesis.

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LIST OF ABBREVIATIONS

PHEV:	Plug-In Hybrid Electric Vehicle
V2G:	Vehicle-to-Grid
NYISO:	New York Independent System Operator
NYMA:	New York Metropolitan Area
ARIMA:	Autoregressive Integrated Moving Average (Model)

CHAPTER 1

Using Vehicle-to-Grid Technology for Peak Load Reduction and Regulation in the New York Metropolitan Area

Introduction

Plug-in Hybrid Electric Vehicles (PHEVs) are the next stage of evolution for today's hybrid car models. PHEV technology expands on the current generation of hybrid vehicles by allowing the vehicle to charge its battery while stationary using the electricity grid. A PHEV can be operated using only the electric motor for several miles, so that the combustion engine does not even turn on for short trips. Widespread PHEV (and Full-Electric Vehicle) use will have substantial effects on electricity use and the electric grid, offering both challenges and potential opportunities for both PHEV owners and grid operators.

While PHEV use will certainly increase the overall electricity load, it offers the potential to act as a distributed storage device and can provide several vehicle-to-grid (V2G) services. The focus of this paper will be on two of these V2G services: peak shifting and ancillary services. As peak shifting devices, PHEV batteries may be charged in periods of low electricity demand (and thus low prices) and discharged during high demand (and high price) periods. Not only can the PHEV owners make a profit by buying energy when the cost is low and selling when the price is high, but doing this can have the effect of decreasing the use of low-efficiency, high-emission peaking units. "Ancillary services" is a more broad term, which can refer to services provided to the electric grid such as frequency regulation or electric reserves. While there is certainly potential for V2G technology to be used as reserves (spinning reserves in particular), the focus of this paper is on frequency regulation, which refers to the adjustments to electricity supply (both up and down) that power system operators must make in order to balance electricity supply and demand in real-time. In this paper, the potential profits to PHEV owners who participate in a program that uses V2G for peak shifting are compared with the potential profits to PHEV owners who participate in a program that uses V2G technology for frequency regulation.

There has been previous research in each of these areas. Several recent papers have shown that there is the potential for significant economic return for using V2G as a frequency regulation provider (Tomic & Kempton, 2007; Quinn, Zimmerle, & Bradley, 2010; Ramteen & Denholm, 2009). Additionally, another recent paper shows that there is very little return for PHEV owners if they were to use V2G exclusively for peak load reduction (Peterson, Whitacre, & Apt, 2010a). These are similar to the findings presented here. While it is important to analyze these separately, it is shown in this paper that these two uses for V2G technology are not necessarily mutually exclusive. It is proposed here that V2G technology can be used for frequency regulation on a daily basis, and additionally be used for peak load reduction during times of extremely high electricity demand and poor ambient air quality. This framework ensures that drivers experience sufficient economic return for their participation in the V2G service, and simultaneously provides environmental benefits during the times in which it is needed most. Additionally, it is possible in certain scenarios that this dual-use V2G service could actually provide higher profits to the participants than either of the single-use V2G programs on their own.

In order to get to the analysis of the dual-use V2G service that is proposed here, the two single-use V2G programs area analyzed individually. For the analyses that follow, a set of general assumptions is required. Firstly, it is assumed that all of the V2G participants are aggregated into a single controllable power resource as described in (Quinn, Zimmerle, & Bradley, 2010). Though it is recognized that it would be necessary for the aggregator to earn some percentage of the profits, no specific assumptions are made about the amount of profits they would earn; instead, the total profits that would accrue to the individual before any percentage of that is taken by the aggregator are presented. Furthermore, the specifications of the upcoming Chevrolet Volt is used as a basis for the analysis to follow. The Volt has a 16 kWh lithium-ion battery that uses a 50% depth-of-discharge; meaning only 8 kWh of the energy on the battery is available for both driving and any V2G use. The 8 kWh of the battery charges fully in approximately six hours, which implies a charge rate of approximately 1.33kW, given the assumption of a constant charge rate. The full-electric range of the vehicle is 40 miles, meaning the vehicle can drive 5 miles per kWh (2011 Volt, 2010). Finally, for much of the economic analysis, it is assumed that the aggregated V2G service is a price taker, having no significant effect electricity loads or prices. This assumption is essentially the same as assuming there is a very low rate of participation in the V2G program. This assumption will be relaxed in Chapter III, where the impacts of high participation rates are discussed

V2G for Peak Reduction

Calculating the amount of peak load that can be reduced through V2G, as well as calculating the profits available to the individual requires specifying the amount of energy that each vehicle will be able to sell to the grid. The National Household Transportation Survey (USDOT, 2002) provides data on the average number of miles driven per day by a sample New York residents. Using this data, the percentage of individuals who fit into each of five groups depending on the average number of miles driven per day is calculated. It is assumed that every member of each of these groups drives the average number of miles driven by that group, and that any electricity not spent on driving is available for V2G. The percentage of individuals that exist in each of these groups as well as the available electricity left on the vehicles in each of these groups are shown in Table 1.

Table 1: Description of Driver Groups

Driver Group	Percentage of Drivers Within Each Range	Average Number of Miles	Available kWh per Vehicle
0 – 10 Miles	22.18 %	4.38	7.124
10 – 20 Miles	20.31 %	14.84	5.031
20 – 30 Miles	20.71 %	25.33	2.934
30 – 40 Miles	13.95 %	33.61	1.278
40+ Miles	22.86 %	59.39	0

The groups of drivers presented in Table 1 will be referred to several times throughout the paper, as the potential profits for the drivers who exist in each of these groups are calculated. As expected, the individuals who are part of the higher mileage groups, and thus have the least spare energy to sell to the grid, will receive the least profits. Left out of the rest of the analysis are those individuals who average more than 40 miles per day and thus are not able to participate in a V2G program.

In 2006, the New York City Department of Transportation estimated that there are approximately 1,130,002 commuters into New York City on a daily basis (Sadik-Khan, 2007). Using this figure, and those presented in Table 1, the potential that V2G technology has for reducing peak electricity load in New York City can be calculated. With 1% of all New York City commuters participating in the program, there is about 38.28MWh of available power. The relationship between participation rate and the amount of power available is linear, such that with 10% of all commuters participating, there is approximately 382.8MWh of available power, and so on. To reiterate what was said earlier, a low participation rate is used for much of the analysis to follow so that there is no effect of changes in electricity load on prices. The implications that result from high participation scenarios will be discussed in Chapter

III. To describe the potential profits for participating in a V2G program that is solely used for peak reduction, refer to Equation 1.

Equation 1: Profits under V2G for Peak Reduction

$$\Pi = R_{en} + R_c - (C_f + C_{en} + C_d)$$

Where:

Π: The total annual profits from V2G participation

R_{en}: The total annual revenue gained from the energy market

R_c: The total annual revenue gained from the capacity market

C_f: The annualized fixed cost of upgrading a vehicle to V2G-capability

C_{en}: The annual cost of purchasing energy that will be sold back to the grid

C_d: The annual cost of battery degradation

Note that each of these costs and revenues are calculated as they apply to the amount of electricity sold to the grid by each vehicle as described in Table 1. Referring back to Equation 1, R_{en} and C_{en} can be viewed in tandem, as they are calculated in a similar manner. Hour-ahead Locational-Based Marginal Pricing (LBMP) data from the New York ISO for the New York City region in the years of 2007, 2008, and 2009 is used to come up with the estimates presented here (NYISO, 2009a). In the calculations of R_{en}, it is assumed that electricity will be discharged while people are at work, since these are the hours that generally experience the highest electricity loads and prices. To calculate R_{en}, the maximum electricity price for each work day is multiplied by the amount of electricity that is available to be sold to the grid, and then summed up over the year. To determine C_{en}, the vehicles are assumed to be charged during the six hours of the night that generally have the lowest electricity prices (12AM through 5AM). The average price over these six hours is defined as the charging price for each day. Thus, the annual cost of energy is the amount of spare electricity on each vehicle multiplied by the charging price at each day, and then summed over the year. The energy revenues, energy costs, as well as the difference between these (energy arbitrage profits) are presented in Tables 2-4. Note that energy arbitrage profits simply refer to $(R_{en} - C_{en})$, the total profits for the V2G-for-peak reduction program are shown in Table 6.

In this analysis, it is assumed that the aggregated V2G service is essentially being compensated as if it were a power generator. Because of this, the V2G participants should be eligible for a capacity payment just as power generators are. Because the V2G service is acting as a peaking generator, (only supplying energy during the hours of highest demand) one would think that like a peaking generator, the capacity payment would make up the majority of their profits, and this is indeed what is found. The problem, however, lies in defining the capacity of a PHEV; capacity for power generators is defined as the maximum amount of power that they can generate, and that amount of power can be generated for an indefinite period of time. This is not the case for PHEV batteries, however, which can produce various amounts of power, but for only as long as the battery lasts. For this reason, the capacity of the aggregated V2G service is defined as the amount of electricity load that the V2G service has the ability to reduce (without causing the load at the peak to actually dip below that of its surrounding hours).

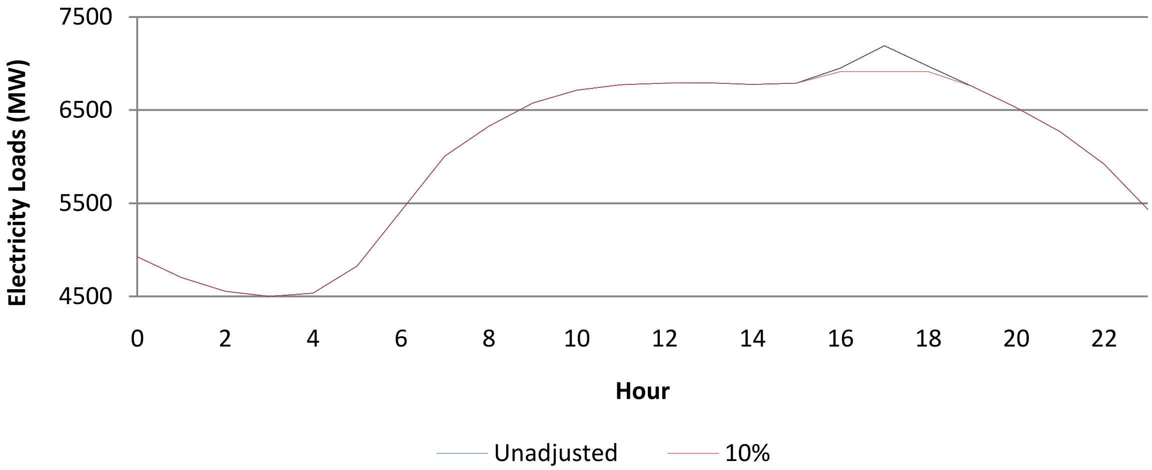

Figure 1: Unadjusted and reduced-peak load with 10% total V2G participation on 1/05/09 **(NYISO, 2009b).**

Figure 1 shows the difference between the unadjusted load and the reduced peak load with 10% total V2G participation (10% of all commuters participate in the V2G program). The way the capacity payment in the V2G program is defined here, it is the distance between the top of the unadjusted peak and the reduced peak at the same hour. Because hourly load data and low participation rates (lower than 10%) are assumed, the capacity (in kW) for each vehicle can simply be defined as the same number of available kWh that is left on the battery. Note that this would not be the case in higher participation scenarios (such as in Figure 2), where the period of peak reduction spans more than one hour. As for the capacity payment itself, a value of $50,000/MW is used, which was approximately the capacity payment that generators received in 2008 (Patton, LeeVanShaick, & Chen, 2008); this value is used for all three years.

The remaining two parts of Equation 1 are C_f and C_d. For C_f, a value of $90 per year is used, as in (Tomic & Kempton, 2007). Though the referenced paper focused on using V2G for frequency regulation, the same technology would be required to use V2G for peak reduction. To determine the cost of battery degradation, refer to Equation 2.

Equation 2: Battery Degradation Costs

$$C_d = \frac{c_b + c_l}{L_c \cdot E \cdot DoD}$$

Where:

c_b: Total cost of a new battery

c_l: Labor cost of battery replacement

L_c: Battery lifetime in number of cycles at a certain depth of discharge

E: Total battery energy capacity

DoD: Depth of discharge used in L_c

Note that in this equation, C_d is the cost of battery degradation in $ per kWh of throughput, which allows for easier interpretation in this type of analysis than would a measure of cost per battery cycle. In Equation 2, c_b is the total cost of a new battery; this is set to $300/kWh, which is the target cost for 2015 set by the U.S. Advanced Battery Consortium (Voelcker, 2007). This number is multiplied by the 16kWh total battery capacity to determine the total cost of a new battery, equal to $4800. c_l is the labor cost of replacing the battery, which is set to$240 (8 hours at $30/hour); this may be somewhat of an overestimate, but it is consistent with the previous literature (Tomic & Kempton, 2007). In the denominator of Equation 2, L_c is the battery lifetime in cycles at a certain depth of discharge. A recent study of the performance of PHEV batteries showed that it took 5300 cycles at 95% depth of discharge before the battery reached 80% of its original capacity (this is the level at which it is recommended to replace the battery) (Peterson, Apt, & Whitacre, 2010b). Unfortunately, data was not available for the number of cycles at 50% depth of discharge, which is the depth-of-discharge employed by the Chevrolet Volt. Given the non-linear relationship between battery lifetime and depth of discharge, using the battery cycle lifetime of 5300 cycles is likely somewhat of a conservative estimate (a higher number is likely the case). In terms of the equation above, L_c is set to 5300 cycles and DoD is set to 95%. E, which is the total energy in kWh on the battery is set to 16kWh. Solving Equation 2, the cost of battery degradation is estimated to be approximately 6.45¢ per kWh of throughput. Shown in Table 5 are the capacity payments and battery degradation costs associated with each driver group (these figures are used for all three years). Finally, the total annual profits for an individual participating in a program that uses V2G exclusively for peak reduction every day of the year are shown in Table 6.

Table 2: Energy Revenues, Energy Costs, and Energy Arbitrage Profits (2007)

Driver Group	Energy Revenues	Energy Costs	Arbitrage Profits
0 – 10 Miles	$364	$148	$216
10 – 20 Miles	$257	$104	$153
20 – 30 Miles	$150	$61	$89
30 – 40 Miles	$65	$27	$39

Table 3: Energy Revenues, Energy Costs, and Energy Arbitrage Profits (2008)

Driver Group	Energy Revenues	Energy Costs	Arbitrage Profits
0 – 10 Miles	$347	$169	$178
10 – 20 Miles	$245	$119	$125
20 – 30 Miles	$143	$70	$73
30 – 40 Miles	$62	$30	$32

Table 4: Energy Revenues, Energy Costs, and Energy Arbitrage Profits (2009)

Driver Group	Energy Revenues	Energy Costs	Arbitrage Profits
0 – 10 Miles	$212	$87	$125
10 – 20 Miles	$150	$61	$89
20 – 30 Miles	$87	$36	$52
30 – 40 Miles	$38	$16	$22

Table 5: Capacity Payments and Battery Degradation Costs

Driver Group	Capacity Payment	Battery Degradation Costs	Fixed Cost
0 – 10 Miles	$356	$163	$90
10 – 20 Miles	$252	$115	$90
20 – 30 Miles	$147	$67	$90
30 – 40 Miles	$64	$29	$90

Table 6: Annual Profits in 2007, 2008, and 2009 – V2G for Peak Reduction

Driver Group	2007 Profits	2008 Profits	2009 Profits
0 – 10 Miles	$319	$281	$229
10 – 20 Miles	$199	$172	$135
20 – 30 Miles	$79	$63	$41
30 – 40 Miles	*-$17*	*-$23*	*-$33*

Notice in Table 6 that the individuals who exist in the group who drive the most (and therefore have the least energy to sell to the grid) actually incur negative profits. The energy costs and battery degradation costs for this group are very low, since they are not contributing much energy to the grid. The primary reason for the negative profits is the fixed capital cost of $90 that is applied to every group of drivers. The differences in profits through these three years are not surprising considering energy prices were at record highs in 2007 and early 2008, then fell considerably with the recession in late 2008. Even with the highest profit figures that are estimated here, it is unlikely that these profits would encourage many individuals to participate in this type of V2G program. In the next section, it is shown that it is far more profitable from the standpoint of the individual to use V2G technology for frequency regulation

V2G for Frequency Regulation

To determine the revenue that could be earned by supplying frequency regulation, one must take into account both regulation up and regulation down. It is assumed here that half of the time spent providing regulation is on regulation up, and half is spent on regulation down. Additionally, it is assumed that the rate of energy exchange for regulation up and regulation down is equal, which implies that the net change in charge of each battery is zero. At the end of any given regulation session, the battery may end up with a charge that is slightly below or slightly above the charge that was left on the battery at the beginning of the session, but in the long run, the net change in charge will approach zero. Additionally, given a V2G-for-regulation program that is aggregated over many vehicles, the difference would likely be too small to cause a significant impact on any individual driver. In order to describe the revenues associated with using V2G for regulation, refer to Equation 3, which is a modified version of the equations used in the previous literature (Tomic & Kempton, 2007; Quinn, Zimmerle, & Bradley, 2010).

Equation 3: Revenues under V2G for Regulation

$$r_{Reg} = \left(p_{reg} \cdot P\right) + \frac{1}{2}\left(p_{el} \cdot P \cdot R_{d-c}\right)$$

Where:

r_{Reg}: Hourly revenue gained from providing regulation through V2G

p_{reg}: Price of regulation at the specified hour

P: Power rating of the vehicle

p_{el}: Price of electricity at the specified hour

R_{d-c}: Ratio of contracted power to contracted time during regulation-up

In some energy markets, different prices are given for regulation up and regulation down; in the market in New York, however, only one price for regulation is given. For this reason, only one equation describing the revenues from regulation is required. The first term in Equation 3 describes the hourly revenue gained through the regulation market. The second term in the equation describes the revenue gained through selling small amounts of electricity to the grid while providing regulation-up. Note that in the previous literature, the same basic formula is used to describe regulation-up, but it is accompanied by another equation for regulation down. Using only one equation and one price for regulation and applying the assumption that half of the contracted time is spent on regulation-up and half on regulation-down, it is necessary to divide the second term in Equation 3 by two.

In terms of conducting the analysis, Equation 3 is applied to each hour of the day during the three years included in the analysis, and then summed over the year. The data used for the regulation prices is the hour-ahead regulation prices for the East region in New York State taken from the NYISO (NYISO, 2009c). The power rating of the vehicle that is chosen is crucial in determining the overall profits from using V2G for regulation. This analysis is conducted for two different power ratings; the first being equal to the actual charge rate of the Chevrolet Volt of 1.33kW. In the context of a PHEV, providing regulation-down is the same as charging the vehicle, and thus the capacity for providing regulation-down is limited by the charge rate of the vehicle. For the purposes of simplification, the assumption that this limitation extends to regulation-up as well is made. Also presented are results for a charge rate of 10kW, as in (Quinn, Zimmerle, & Bradley, 2010), which implicitly assumes that faster charging technology will be available by the time V2G technology is ready for deployment. The electricity prices that are used here are the same LBMPs that were used in the previous section. Finally, the R_{d-c} term is set equal to 0.10, as in the previous literature; this implies that the regulation provider is actively selling energy to the grid (at their full regulation capacity) for 10% of the time during which they are contracted for regulation-up (Tomic & Kempton, 2007; Quinn, Zimmerle, & Bradley, 2010). Because the NYISO has only a single market for regulation (not markets for regulation up and down), the second term in Equation 3 is divided by two such that

5% of the total contracted time for regulation is spent actively selling energy to the grid at the full regulation capacity.

Furthermore, to more accurately estimate annual revenues, an hourly measure of vehicle availability is required. To do this, data from the Regional Travel – Household Interview Survey (RT-HIS) in the New York Metropolitan Area is used to determine the percentage of commuter vehicles that are parked and available for V2G at each hour (NYDOT, 2000). The RT-HIS provides data on the percentage of commuters going to and from work at each hour. Using the assumption that each commuter that is going to work then spends eight hours working, and the assumption that all individuals are either commuting (not available) or are parked at work or home (available), an approximate measure of the percentage of individuals who are parked either at work or at home (and are presumably available for V2G) at each hour can be computed. Although this does not provide an actual driving pattern of any real individual, it provides a measure of vehicle availability for an "average" individual. The minimum availability is approximately 77.9% at 6AM, and the maximum is approximately 99.8% at 1AM. Over the 24 hour period, the availabilities sum to approximately 22 hours.

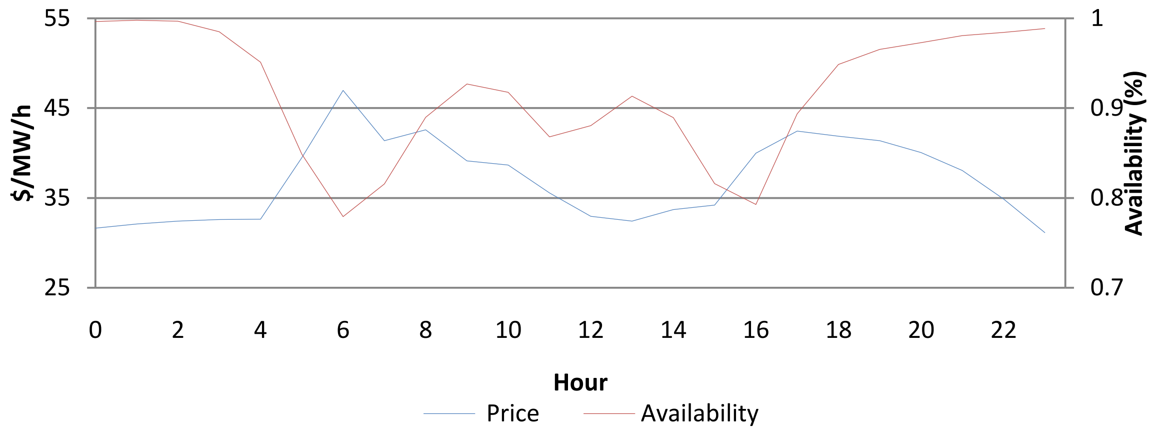

Figure 2: Average hourly regulation prices for the East region in New York State in 2009 and hourly vehicle availability percentages

Figure 2 helps to illustrate the motive behind using hourly vehicle availability; a measure for average hourly revenue could have been used here and simply been multiplied by 22 hours, but this would provide somewhat of an overestimate since the hours of lowest vehicle availability tend to coincide with the hours with the highest regulation prices. On the other hand, if zero availability during the commuting hours and 100% availability during the remaining hours were assumed, this would result in an underestimate. Additionally, it is likely that this effect will be exacerbated with higher penetrations of PHEVs: the load will be even more variable at the commuting hours, which should raise the price of regulation. To determine the total annual revenue obtained through the V2G-for-regulation program, the hourly revenues described in Equation 3 are multiplied by the percentage of available vehicles at each hour, and then summed over the year. The annual revenue calculations for 2007, 2008, and 2009 as described in Equation 3 are shown in Table 7.

Table 7: Regulation Revenues (2007, 2008, and 2009)

Power Rating	Revenue (2007)	Revenue (2008)	Revenue (2009)
10kW	$4780	$4666	$3203
1.33kW	$637	$622	$427

The costs of participating in a program that uses V2G exclusively for frequency regulation are very similar to the costs of using V2G for peak reduction. The costs are separated into three categories: fixed capital costs, energy costs, and the cost of battery degradation. Because the same basic technology is needed for the vehicle upgrade, the fixed costs are assumed to be exactly the same as they were in the previous section: $90 annually. The energy cost associated with using V2G for regulation is the cost of purchasing energy that will later be sold to the grid while the vehicle is providing regulation-up. Given the assumption of a net zero change in battery charge, however, the energy that is sold to the grid is exactly offset by the "free charging" experienced while providing regulation down; thus, the implied net cost of energy is zero.

There are some uncertainties when estimating the costs of battery degradation specifically in the case of V2G for regulation. The reason for this uncertainty is that the nature of regulation implies that the battery will experience repeated charging and discharging in rapid succession. This may sound like it would degrade the battery, but the fact of the matter is that it has been shown that charging at a shallow depth of discharge can exponentially increase the cycle life of a battery (Peterson, Apt, & Whitacre, 2010b). With such long cycle lives at such a shallow depth of discharge, one could make the case for very low or even zero cost of battery degradation. A somewhat more conservative approach is taken here, however, and a scaling factor of three is used (the same assumption that has been employed by previous authors (Tomic & Kempton, 2007; Quinn, Zimmerle, & Bradley, 2010)). This means that the shallow discharging results in three times the cycle life, and thus one third of the cost in dollars per kWh of throughput when compared with deep discharging. The cost of battery degradation in this case is 2.01¢ per kWh of throughput. Total annual vehicle throughput is calculated by using the vehicle availability percentages along with

$P \cdot R_{d-c}$ from Equation 3. The annual battery degradation costs for the 10kW and 1.33kW scenarios are \$167.46 and \$22.33, respectively. The battery degradation costs as well as the fixed cost of upgrading the vehicle are subtracted from the annual revenues to determine the total annual profits from participating in a program that uses V2G exclusively or regulation, these results are presented in Table 8.

Table 8: Annual Profits for 2007, 2008, and 2009 – V2G for Regulation

Power Rating	2007 Profits	2008 Profits	2009 Profits
10kW	\$4656	\$4616	\$2951
1.33kW	\$543	\$537	\$316

It is shown here that even with the least generous assumptions, the profits experienced while participating in a V2G-for-regulation program are greater than even the highest profits earned in a program that uses V2G for peak reduction in the same year. Additionally, if a power rating of 10kW (or close to it) becomes possible with fast-charging technology, there is potential for V2G-for-regulation participants to experience extremely large profits. In the next section, a combined V2G program is presented in way such that the higher profits that are realized by using V2G for regulation are kept intact, while still achieving some of the external benefits associated with peak reduction by only using V2G for peak reduction on the days when it is needed most.

V2G for Peak Load Reduction and Regulation

When it comes to using V2G technology for peak load reduction, there are limited financial incentives for the driver. That being said, there is potential for significant external benefits if V2G is used for peak reduction during times of high electricity demand. These external benefits come in the form of cost savings for the grid operators, who may be able to decrease the use of expensive and inefficient generators. Additionally, there may be significant environmental benefits that can be experienced. Periods of high electricity demand typically happen during hot summer days; the damage from additional power plant emissions on these days tends to be exacerbated by the atmospheric conditions during these times, which are conducive to the formation of certain air pollutants, such as ozone (USEPA, 2006).

Because of the higher profits that are available, it is assumed that the V2G participants are exclusively providing regulation for most days of the year. That being said, it is assumed that the participants are always available to sell energy to the grid for the purpose of peak reduction. In a sense, they will end up acting like a traditional peaking generator that only produces electricity when electricity demand is extremely high. In reality, the times that PHEVs would be used to provide peak-reducing energy to the grid would ultimately be up to the grid operator or ISO, but for the purposes of this analysis, it is necessary to specify these times. It will be assumed here that V2G is used for peak reduction only on ozone exceedance days. Using this as a benchmark, the annual profits for a V2G participant in this type of program can be calculated.

An ozone exceedance day is any day when the measured average ambient ozone concentration is above the federal standard (National Ambient Air Quality Standard) of 0.075ppm for an eight hour period or 0.12ppm during a single hour. In this analysis, any day that registered an eight hour ozone exceedance at any of the New York Metropolitan Area monitoring stations (there are nine) is considered. In 2009, there were nine such ozone exceedance days in the New York Metropolitan Area: 26-Apr, 22-May, 7-June, 16-Jul, 10-Aug, 16-Aug, 17-Aug, 26-Aug, and 5-Sep. Additionally, there were 18 ozone exceedance days in 2008 and 11 in 2007 (NYDEC, 2010). In reality, using ozone exceedance days as a benchmark is only useful in retrospect. If this type of program were to be actually implemented, a different system that might use day-ahead air quality forecasts or even day-ahead electricity load forecasts would be required to signal for the use of V2G for peak reduction.

With specific days identified for the use of V2G for peak reduction, it is then possible to estimate the potential profits of a participant in this type of program. The bulk of the profits still come from using V2G for frequency regulation during most of the year. This means that the profits for these days can be computed exactly as they were before. This, however, does not represent all of the profits from the market for regulation because it is possible for the participants to provide regulation even on the peak-reduction days up until the time that they sell their excess energy for the purpose of load reduction. It is assumed here that the V2G participants will provide regulation on exceedance days from 6AM (the time the vehicle is assumed to be fully charged) until the time at which their excess energy will be sold to the grid. As expected, the annual revenues and battery degradation costs are only slightly lower for the regulation component.

When calculating the profits associated with energy arbitrage, the revenues and costs for each of the exceedance days were calculated just as before, but only for the exceedance days instead of every day of the year. To calculate the cost of battery degradation, it was necessary to determine the electrical throughput during both peak reduction and regulation, and then multiply by the associated price. Additionally, the fixed capital cost of $90 is taken into account in each scenario.

The last component to take into account is the capacity payment. Because the vehicles would be available to supply energy to the grid year-round, there is no reason to believe that they would not be eligible for the full capacity payment as described previously. In the type of program discussed here, the V2G participants would essentially be operating in the same manner as a peaking power plant. Many of these peaking power plants do not operate for more than a few days throughout the year (similar to this proposed V2G program). It follows that a V2G program behaving in a similar manner as these peaking power plants would be eligible for similar compensation. All of the components that go into the final profits in the dual-use V2G program are shown in Table 9-14, and the final annual profits for the proposed V2G program are shown in

Table 15-17.

Table 9: 2007 Dual-Use V2G Peak Reduction Profit Components

Driver Group	Energy Revenue	Energy Cost	Arbitrage Profits	Battery Cost (Peak Component)	Capacity Payment
0 – 10 Miles	$23	$5	$17	$5	$356
10 – 20 Miles	$16	$4	$12	$3	$252
20 – 30 Miles	$9	$2	$7	$2	$147
30 – 40 Miles	$4	$1	$3	$1	$64

Table 10: 2007 Dual-Use V2G Regulation Profit Components

Power Rating	Regulation Revenue	Battery Cost (Regulation Component)
10kW	$4521	$165
1.33kW	$603	$22

Table 11: 2008 Dual-Use V2G Peak Reduction Profit Components

Driver Group	Energy Revenue	Energy Cost	Arbitrage Profits	Battery Cost (Peak Component)	Capacity Payment
0 – 10 Miles	$31	$13	$19	$8	$356
10 – 20 Miles	$22	$9	$13	$6	$252
20 – 30 Miles	$13	$5	$8	$3	$147
30 – 40 Miles	$6	$2	$3	$1	$64

Table 12: 2008 Dual-Use V2G Regulation Profit Components

Power Rating	Regulation Revenue	Battery Cost (Regulation Component)
10kW	$4373	$163
1.33kW	$538	$21

Table 13: 2009 Dual-Use V2G Peak Reduction Profit Components

Driver Group	Energy Revenue	Energy Cost	Arbitrage Profits	Battery Cost (Peak Component)	Capacity Payment
0 – 10 Miles	$5	$2	$3	$4	$356
10 – 20 Miles	$3	$1	$2	$3	$252
20 – 30 Miles	$2	$1	$1	$2	$147
30 – 40 Miles	$1	$0	$1	$1	$64

Table 14: 2009 Dual-Use V2G Regulation Profit Components

Power Rating	Regulation Revenue	Battery Cost (Regulation Component)
10kW	$2984	$165
1.33kW	$398	$22

Table 15: 2007 Annual Profits - Dual Use V2G Program

Driver Group	Annual Profits – 10kW	Annual Profits – 1.33kW
0 – 10 Miles	$4634	$859
10 – 20 Miles	$4525	$751
20 – 30 Miles	$4418	$643
30 – 40 Miles	$4332	$557

Table 16: 2008 Annual Profits - Dual Use V2G Program

Driver Group	Annual Profits – 10kW	Annual Profits – 1.33kW
0 – 10 Miles	$4486	$838
10 – 20 Miles	$4378	$730
20 – 30 Miles	$4270	$622
30 – 40 Miles	$4185	$537

Table 17: 2009 Annual Profits - Dual Use V2G Program

Driver Group	Annual Profits – 10kW	Annual Profits – 1.33kW
0 – 10 Miles	$3084	$641
10 – 20 Miles	$2979	$537
20 – 30 Miles	$2874	$432
30 – 40 Miles	$2792	$350

In a recent analysis, Jon Wellinghoff (Chairman of FERC) estimated the long run costs of owning several vehicle types (Wellinghoff, 2009). The purpose of this analysis was to point out that the net present value of a "CashBack" PHEV (a PHEV used for V2G) can actually decrease over time. Using estimated annual V2G profits of $1500, the net present value of the "CashBack" PHEV (which has much higher initial costs) dipped below all other types of automobiles (gasoline internal combustion included) after approximately four years. Given the numbers presented here (in both the V2G-for-regulation and combined scenarios), it would take a slightly higher charge rate than the standard charge rate of the Chevrolet Volt to achieve the type of "CashBack" car presented in Wellinghoff's analysis. Achieving a charge rate sufficient to provide at least $1500 in annual profits seems to be very possible in the near future (though 10kW will likely take longer). The fact that a PHEV used for V2G could actually become less expensive than a traditional automobile after just a few years seems to be quite promising in terms of the near-term adoption of both PHEVs and V2G technology.

Along the same lines as Wellinghoff's analysis, shown in Table 18 are the annual fuel costs of driving a gasoline internal combustion engine automobile (assuming a gasoline price of $3.00/gallon and 30mpg fuel efficiency) compared with the annual fuel cost (using 2008 electricity prices) of driving a PHEV with and without V2G (the profits used here are from the dual-use V2G program).

Table 18: Annual Fuel Cost - Internal Combustion and PHEV Comparison

Driver Group	Avg. Daily Miles Driven	Internal Comb-ustion	PHEV (No V2G)	PHEV (1.33kW V2G)	PHEV (10kW V2G)
0 – 10 Miles	4.38	-$160	-$22	+$619	+$3062
10 – 20 Miles	14.84	-$542	-$75	+$462	+$2904
20 – 30 Miles	25.33	-$924	-$129	+$303	+$2745
30 – 40 Miles	33.61	-$1227	-$171	+$179	+$2613
40+ Miles	59.39	-$2168	-$910	N/A	N/A

Notice in Table 18 that even in the case of PHEVs with no V2G technology being used that the annual fuel costs are drastically below that of a gasoline internal combustion automobile. Additionally, notice that the annual fuel costs for PHEV drivers in the 40+ mile range increase dramatically; this is due to the fact that only the first 40 miles can be driven without the use of gasoline. If V2G technology is taken into account, there are significant profits in place of the annual fuel costs, further reinforcing the idea that the use of PHEVs for V2G could increase the incentive for people to start switching away from internal combustion automobiles in the relatively near term.

Back to the analysis at hand, notice in Tables 15-17 that some of the profits for the combined-use V2G program are actually higher than the profits for either single-use program on their own in 2009. The reason that the profits are higher than the V2G for regulation program by itself is that the V2G system is only being used for peak reduction on a very limited number of days, and the additional capacity payment received more than makes up for the lost revenues that are experienced when the vehicles are being used for peak reduction rather than regulation. In 2007 and 2008, where there were more exceedance days, and thus more days where the V2G program was being used for peak reduction, the profits in the combined program are generally lower than the regulation-only program. This is not necessarily a problem, however, since the profits only need to be high enough to incentivize people into participating in the program. In fact, with more days being used for peak reduction, the profits to the individual may be lower, but the external benefits could be higher. An unexpected long-run problem is possible if the profits are actually too high, and too many people want to participate in the program. The effects of high penetrations of PHEVs and high participation in a V2G program are discussed in Chapter III. One of the effects of high PHEV penetration and V2G participation is that electricity prices will be altered. In order to estimate these effects, an econometric model is necessary to predict the effect of changes in loads on electricity prices. The model that predicts electricity prices is described in Chapter II.

CHAPTER 2

Electricity Price Prediction Model

The purpose of the model presented here is to estimate electricity prices given electricity loads and other factors that influence price. This is done in a two step process where the first model predicts electricity loads, and then a second model is used to estimate electricity prices given the predicted loads from the first model. The research presented here is based upon previous work by Jaeuk Ju (Ju & Mount, 2009) and Jung Youn Mo, who have each created similar models, though estimated in different ways. The models that are presented here distinguish themselves mainly in the way that the hour of the day is taken into account. The previous models were estimated either using average daily price and load data or using a single hourly time series to produce their results. The models presented here, however, are specifically aimed toward taking the hour of the day into account. One way of doing this would be to have a single model that has dummy variable for each hour of the day. The approach taken here is to actually have twenty-four different models, each one representing a single hour of the day such that each observation in each of the sets of data represents one day. Each set of models in the two-step process will be presented separately; the models that predict electricity load are presented first.

Electricity Load Estimation

The data used to estimate this model contains two years (2007 and 2008) of hourly data for the electricity load in New York City (NYISO, 2009b) as well as hourly local temperature data. Because only one hour of each day will be used to estimate each model, there are 731 observations for each model to be estimated (731 because 2008 was a leap year). Before getting into a description of the data, it will be useful to have a simplified version of the model to use as reference. The simplified model is presented as follow:

Equation 4: Simplified Electricity Load Model Description

$$\begin{aligned} ln(Load) = \alpha + \beta_1 \cos(h) + \beta_2 \sin(h) + \beta_3 \cos(1) + \beta_4 \sin(1) + \beta_5 mon + \beta_6 tues + \beta_7 wed \\ + \beta_8 thur + \beta_9 fri + \beta_{10} sat + \beta_{11} hol + \beta_{12} CDD + \beta_{13} CDD^2 + \beta_{14} HDD \\ + \beta_{15} HDD^2 + \beta_{16} ln(Load_{One\ Hour\ Lag}) + \beta_{17} ln(Load_{One\ Day\ Lag}) \end{aligned}$$

The dependent variable in this model is the natural log of electricity load in New York City at a given hour. As discussed before, each period in the time series represents one day, and the electricity load is that of a single hour in that day. This means that the value for $Load_{t-1}$ in each model is the previous day's load at that hour, which is represented by $Load_{One\ Day\ Lag}$ in Equation 4. Also included in the model is $Load_{One\ Hour\ Lag}$, which is the electricity load on that day, at the previous hour. For example, if in a particular observation *Load* represents the electricity load at 3:00 on Tuesday, $Load_{One\ Hour\ Lag}$ represents the load at 2:00 on Tuesday, and $Load_{One\ Day\ Lag}$ represents the load at 3:00 on Monday.

The first four measured independent variables in the model: *cos(h), sin(h), cos(1),* and *sin(1)* are the seasonal variables in the model, where the first two are cosine and sine curves with half year cycles, and the second two are cosine and sine curves with full year cycles. The reason that both cosine and sine curves are necessary here is that there are two periods in the year when load is substantially higher than normal. The period of highest increased demand is in the summer, when additional electricity is used for cooling, and the other period of increased demand is in the winter, when the load rises because of heating. Equation 5 describes how these variables are calculated. Note that in the equations, *t* represents the number of the time-series observation, where each observation is one day. Additionally, note that the one-year seasonal variable is divided by 365.5 (and the half-year variable by 182.75) because of the fact that 2008 was a leap year. The sine variables are calculated in exactly the same manner, with a sine function replacing the cosine function.

Equation 5: Definitions for *cos(1)* and *cos(h)*

$$cos(1) = cos\left(\frac{2 \cdot \pi \cdot t}{365.5}\right)$$

$$cos(h) = cos\left(\frac{2 \cdot \pi \cdot t}{182.75}\right)$$

The next six variables in the model: *mon, tues, wed, thur, fri,* and *sat* are dummy variables, each representing a day of the week. The variable that is left out represents Sunday, so that all of the coefficients on the other days will be comparing the electricity load on that day to the load on Sunday. The next variable: *hol* is another dummy variable, which is set to one during all national holidays.

The last variables left to describe: *CDD, HDD,* CDD^2, and HDD^2 represent temperature, where *CDD* means cooling degree days and *HDD* means heating degree days. Because of the nonlinear relationship between temperature and load, a simple measure of temperature cannot be used here. It is assumed that any temperature below 65˚F will be accompanied by additional heating demand, while any temperature above 65˚F will be accompanied by additional cooling demand.

Equation 6: Definitions for *CDD* and *HDD*

$$CDD = max(T - 65, 0)$$

$$HDD = max(65 - T, 0)$$

Equation 6 describes how the *CDD* and *HDD* variables are calculated. With the variables defined this way, if the temperature were 75˚F at a particular observation, it would result in values of *CDD = 10*, and *HDD = 0*. Alternatively, if the temperature were 55˚F, it would result in values of *CDD = 0*, and *HDD = 10*. Additionally, quadratic terms of each of these variables are included in the model. The reason for this is because as the difference between *T* (measured temperature) and 65˚F increases, the load will likely increase at an increasing rate.

To expand on the simplified model shown above, the actual model to be estimated is specified as an ARIMA model. In order to determine the orders of the Autoregressive and Moving Average processes, a measure of fit (Bayesian Information Criterion) is determined for 16 specifications of each of the 24 models. Table 19 shows the BIC for each of these specifications at the 0^{th} hour (12:00 midnight).

Table 19: Bayesian Information Criterion Results

MA↓ AR→	0	1	2	3
0	-5124.678	-5147.384	-5141.675	-5119.747
1	**-5148.903**	-5142.358	-5135.951	-5137.249
2	-5142.347	-5135.802	-5136.306	-5131.185
3	-5119.553	-5136.905	-5131.649	-5125.094

This shows that the model achieved the greatest fit (minimum-BIC) at an AR(0)/MA(1) model specification. Although this was not the minimum-BIC specification for every hour, it was the most common. For this reason (and for the sake of continuity), the AR(0)/MA(1) specification is used to estimate all 24 hours. Note that because it is a 0^{th} order autoregressive model, it is no longer an ARIMA process, but a multiple variable MA(1) model. The final version of the model is shown in Equation 7.

Equation 7: Final Electricity Load Model Specification

$$\begin{aligned} ln(Load) = \ & \alpha + \beta_1 \cos(h) + \beta_2 \sin(h) + \beta_3 \cos(1) + \beta_4 \sin(1) + \beta_5 mon + \beta_6 tues + \beta_7 wed \\ & + \beta_8 thur + \beta_9 fri + \beta_{10} sat + \beta_{11} hol + \beta_{12} CDD + \beta_{13} CDD^2 + \beta_{14} HDD \\ & + \beta_{15} HDD^2 + \beta_{16} ln\left(Load_{One\ Hour\ Lag}\right) + \beta_{17} ln\left(Load_{One\ Day\ Lag}\right) + \varepsilon_t \end{aligned}$$

Where $\varepsilon_t = u_t + \theta u_{t-1}$, and u_t is a white noise residual uncorrelated with u_s $(\forall\ s \neq t)$

Results: Load Estimation

Because there are 24 different models being estimated here, it would be rather cumbersome to report all of the coefficients for each model; instead, graphs tracking the coefficients for each of several key variables will be presented (all of the coefficients and z-statistics are shown in the appendix). Before getting into the individual variables, it will be useful to analyze a measure of fit. Presented in Figure 3 is a graph of the Bayesian Information Criterion (the same measure that was used for order selection).

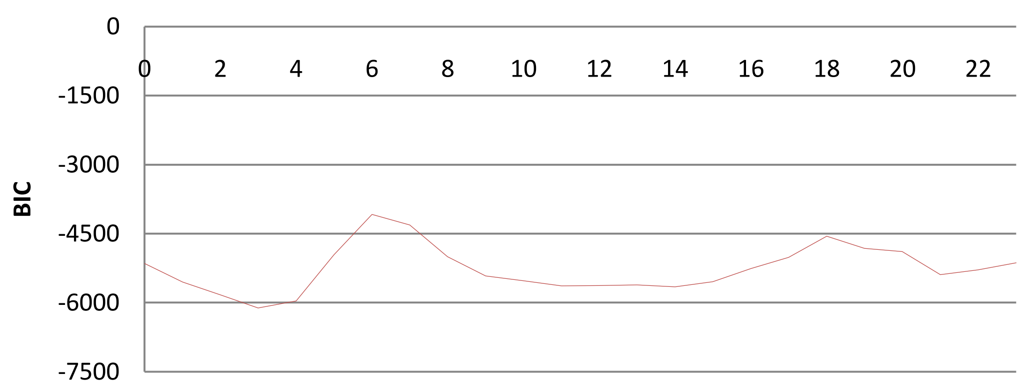

Figure 3: Bayesian Information Criterion (Load Estimation)

The high negative values for the BIC are indicative of good fit. The most interesting item to note about this graph is how the fit is best (highest negative value) during the hours of the day with relatively constant electricity demand; during the hours with a lot of ramping (up or down), the fit decreases due to the increased difficulty in predicting electricity load. The first and probably the most important variable that will be presented is the one hour lagged electricity load, shown in Figure 4.

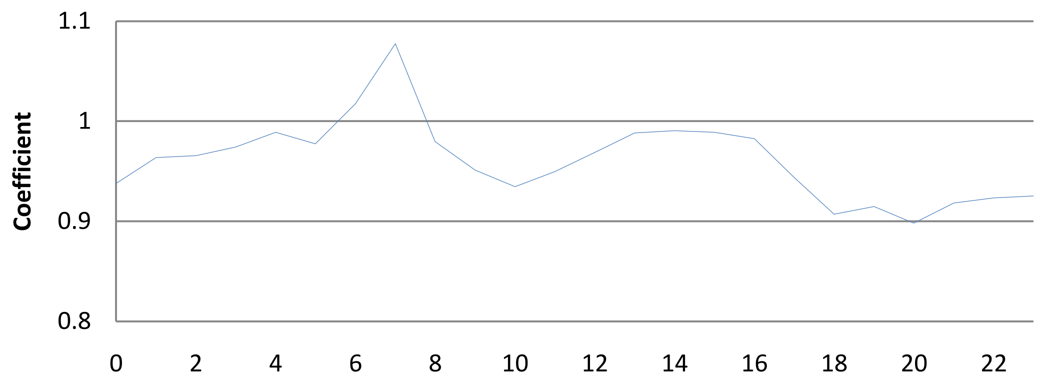

Figure 4: One Hour Lagged Electricity Load

The reason this variable is shown first is because it illustrates a problem that will persist throughout the rest of the analysis. There are two hours (6:00AM and 7:00AM) for which their one hour lagged electricity coefficients are greater than one; additionally, each has a root that is greater than one. This suggests that observations that are farther in the past at these hours are actually more important than recent hours when it comes to predicting the electricity load. Note that for these two hours, more complicated versions of the model were tested (with higher AR and MA orders), but none resulted in significant changes in the coefficients, and certainly none less than one. Although that was not the result that was sought, it does act as a sort of robustness test for the models, implying that the model is not overly sensitive to changes in its specification.

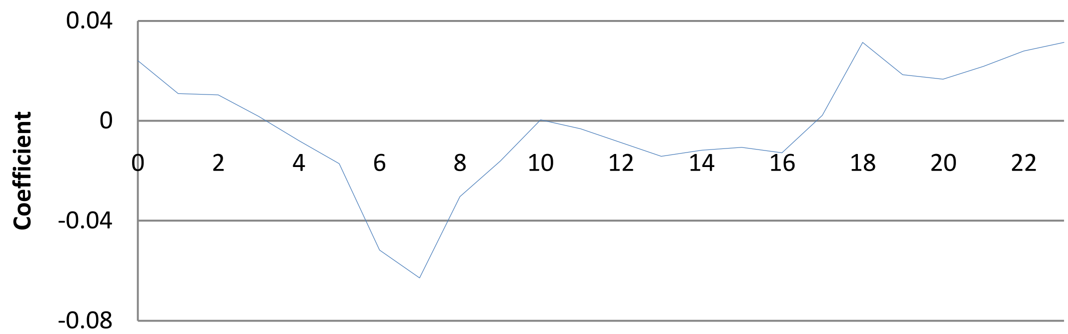

Figure 5: One Day Lagged Electricity Load

The variable shown in Figure 5 is the 24-hour lagged electricity load. Again, there is some inconsistent behavior happening during the hours of 6:00AM and 7:00AM, which is to be expected after looking at the results of the one-hour lagged load coefficients. Both the one-hour and 24-hour lagged electricity variables show significance during most hours; the one-hour lagged variable has a minimum z-statistic of 70.84 at 6:00AM, and has z-statistics well above 100 for most of the other hours. The 24-hour lagged variable has a z-statistic close to 4 for most hours, though there are some hours (when the coefficient estimate is close to zero) that the z-statistic is very low, such as 10AM where the z-statistic was equal to 0.11). This is merely because the variance stays relatively constant throughout the 24 hours, so it would be expected that when the coefficient estimate is near zero, low significance would be reported. Figure 6 is a combination of the one-hour and the one-day lagged coefficients, it shows the one hour lagged coefficient plus the one day lagged coefficient, minus the product of the two. For a single well behaved model one would expect that this value to be below one, which is what happens for the majority of the hours. That being said, both the 6:00AM and 7:00AM values are above one, which further reinforces the suggestion that the models for these hours are not well behaved, and are counting past values of electricity load as more statistically important than recent values.

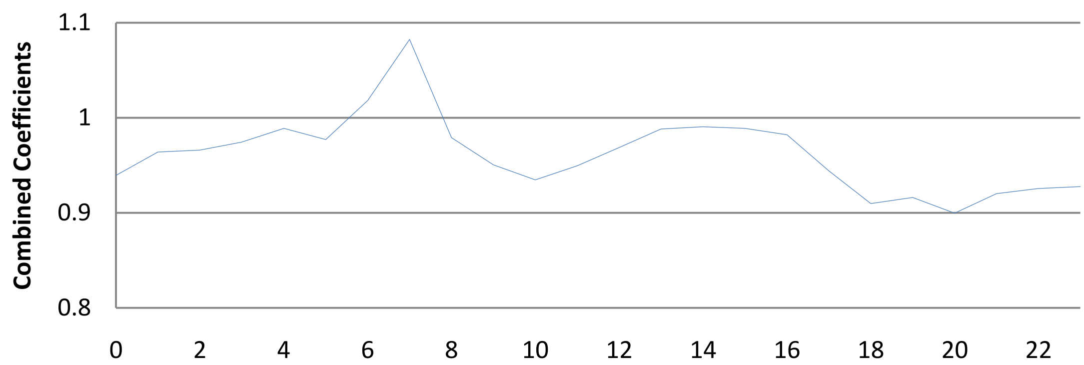

Figure 6: $\boldsymbol{\beta_{16} + \beta_{17} - (\beta_{16} \cdot \beta_{17})}$

It is extremely important to keep in mind the anomalies at 6:00AM and 7:00AM as the other variables are analyzed. It is shown that the estimated coefficients at these hours are inconsistent with the other hours for each of the variables to be analyzed. Presented in Figure 7 are the estimated coefficients for the Wednesday, Saturday, and Holiday variables.

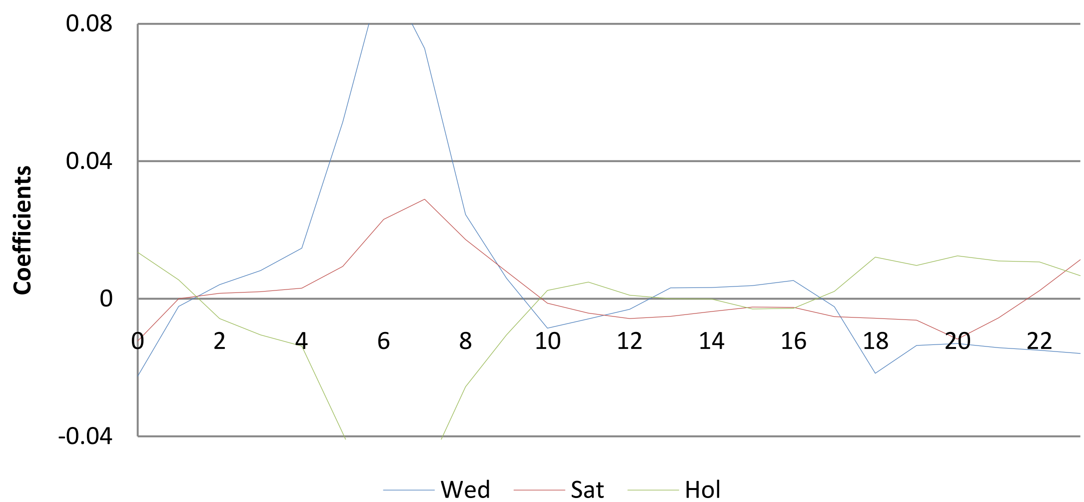

Figure 7: Wednesday, Saturday, and Holiday Coefficients (Load Estimation)

Though the only weekday variable that is shown here is Wednesday, it should be noted that all of the other weekday variables produced estimates that are extremely close together, such that choosing one of them provides a good representation of all of the weekday variables. Additionally, though the coefficient estimates in Figure 7 appear to be close to zero for many hours, the holiday variable and all of the day-of-the-week variables show strong significance during almost every hour (except a small number of hours near when the coefficient estimates change sign). These variables behave generally as expected during most hours (recall that the day-of-the-week variables are compared being compared to Sunday). The weekday variables are positive during most of the hours associated with peak electricity demand, implying that electricity load is generally higher during these times on weekdays. As for the holiday variable (which is set to one during holidays), the coefficient estimates are near zero or negative for most of the mid-day peak electricity hours, and then positive during the evening hours, which would likely be expected. The coefficient estimates for the Saturday variable are a bit less understandable, as they predict lower electricity load for nearly the whole day. The last set of variables to be analyzed in-depth are the cooling and heating degree variables. Because both the unadjusted variable and the quadratic version of each variable were included, the coefficient estimates for each variable on their own do not reveal much; it is much more illuminating to analyze the net effect of the combination of each set of variables on electricity load.

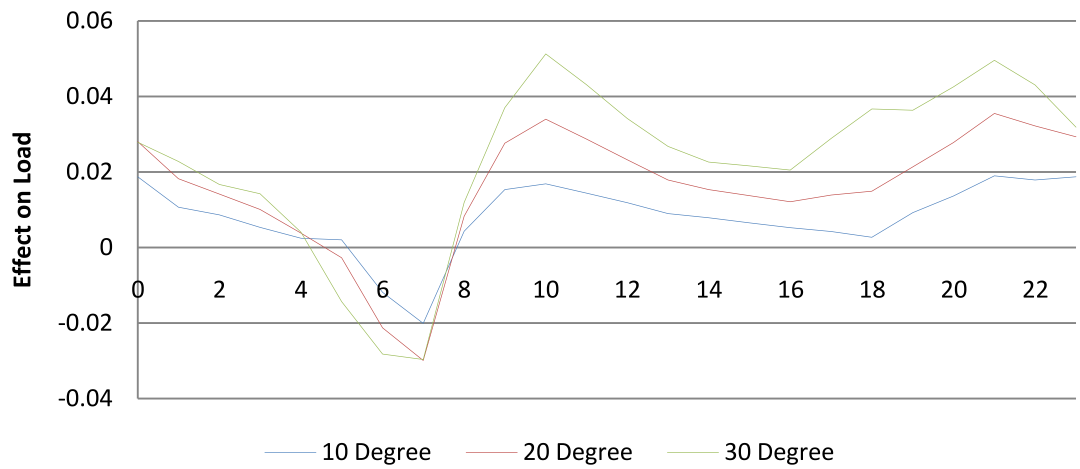

Figure 8: Cooling Degree Day Net Effect on Load

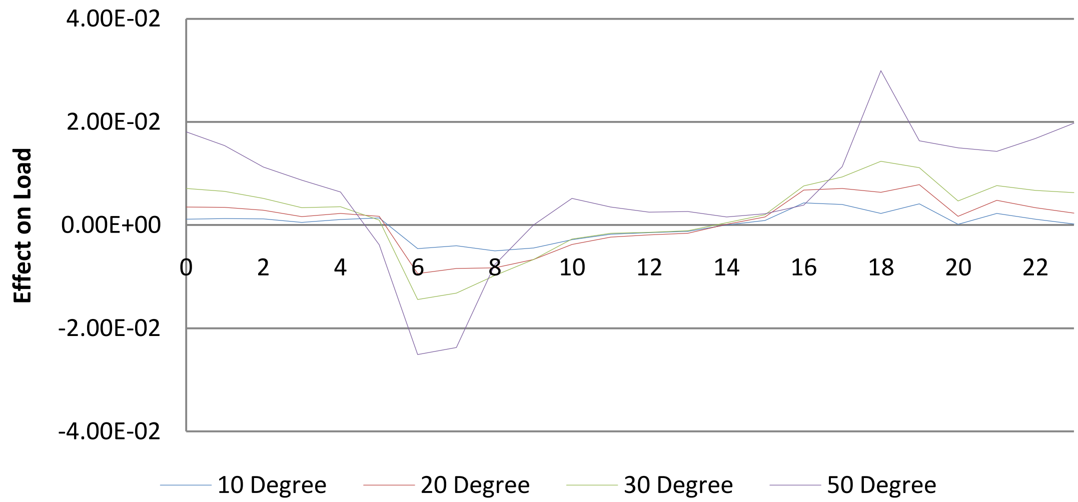

Figure 9: Heating Degree Day Net Effect on Load

The effects of cooling shown in Figure 8 behave in a way that is very logical, where the largest effects on electricity load occur during the hours when the work day tends to start, and in the hours when many people are coming home from work. Note that because these are not coefficient estimates, they cannot be interpreted in the same manner. For instance, the line in Figure 8 that represents a 30 degree cooling day shows what the effect on electricity load would be if it were 95 degrees at each specific hour. This is the reason that it is logical to think the highest effect on load would occur during an hour at the beginning of the work day: if it were 95 degrees at the beginning of the day, it is likely that people would want to increase their air conditioning more than if it were 95 degrees at the hours that typically have the highest temperature. The heating degree effects shown in Figure 9 make slightly less sense for the 10, 20, and 30 degree effects, where the effect on electricity load is shown to be negative for many of the morning hours. That being said, the effect of a 50 degree heating day seems to make perfect sense for just about all of the hours (6:00AM and 7:00AM excluded).

While all of the estimated coefficients for each hour do not necessarily behave exactly as one would expect, they do behave well for the most part, which is about all that can be expected from a set of 24 econometric models. The real test of the model does not come in the estimated coefficients themselves, but in the predictions of electricity load that are provided. As a simple estimate of the predictive power of these models, the average difference between the predicted load and actual load was calculated to be approximately 0.219% (positive and negative differences offsetting), and 0.457% in absolute value.

Electricity Price Estimation

The model that is used to predict electricity prices is very similar to the load estimation model. It is the same in that there are separate models estimated for each hour of the day, and it contains all of the same daily and seasonal variables. The variables that are not necessary in the price model are the variables that are based on temperature. Instead, there are new variables that represent the price of natural gas, which will be discussed in more detail below. Additionally, the predicted loads from the first model are used as an input into the electricity price estimation model. Finally, the price estimation model is also an ARIMA model, though the model specification that resulted in the greatest fit for the greatest number of hours in this case is an AR(1)/MA(1) specification. The model specification for the electricity price prediction model is shown in Equation 8.

Equation 8: Final Electricity Price Model Specification

$$\begin{aligned} ln(Price) = \ & \alpha + \beta_1 \cos(h) + \beta_2 \sin(h) + \beta_3 \cos(1) + \beta_4 \sin(1) + \beta_5 mon + \beta_6 tues + \beta_7 wed \\ & + \beta_8 thur + \beta_9 fri + \beta_{10} sat + \beta_{11} hol + \beta_{12} Load + \beta_{13} Load^2 + \beta_{14} NG1 \\ & + \beta_{15} NG2 + \beta_{16} ln\left(Price_{One\ Hour\ Lag}\right) + \beta_{17} ln\left(Price_{One\ Day\ Lag}\right) + \varepsilon_t \end{aligned}$$

Where $\varepsilon_t = \rho\varepsilon_{t-1} + u_t + \theta u_{t-1}$*, and* u_t *is a white noise residual uncorrelated with* u_s $(\forall\ s \neq t)$

The only variables in Equation 8 that are left to be explained are *NG1* and *NG2*. These are the variables that represent the price of natural gas, which is a particularly important factor in determining the price of electricity in New York City, as many of the generators in the area are fueled by natural gas. It is a reasonable assumption that the price of electricity is affected by both present and past values of natural gas; two weeks' worth of lagged values of the price of natural gas are taken into account.   Instead of including a variable for each day in the two weeks of lagged prices, Lagrange interpolation polynomials are used to reduce the number of variables that need to be included in the model. Furthermore, the Lagrange polynomials have the effect of smoothing the lag structure over the period of lagged values, which is likely much more realistic than the erratic lag structure that would most likely result from using a separate variable for each day in the period of lagged values. To use the Lagrange interpolated polynomials in the econometric model, it is necessary to compute weighted sums of the natural gas prices for each observation. These weighted sums for this model were computed on an hourly basis, such that a lagged value of ($t – 336$) is taken into account. There are actually only 10 natural gas price observations (one for each weekday) in a two week period, so each of the other hourly observations were interpolated. In the calculations of the Lagrange interpolation polynomials, three base points were chosen (*t = 0, t = 168, t = 336*). The polynomials for the lag structure and the weighted sums are calculated as in Equation 9 and Equation 10.

Equation 9: Lagrange Interpolation Polynomials

$$P_{1i} = \frac{(i-168)(1-336)}{(0-168)(0-336)}$$

$$P_{2i} = \frac{(i-0)(1-336)}{(168-0)(168-336)}$$

$$P_{3i} = \frac{(i-0)(1-168)}{(336-0)(336-168)}$$

Equation 10: Lagrange Interpolation Weighted Sums

$$NG_{kt} = \sum_{i=0}^{336} P_{ki} \cdot ln(PNG_{t-i})$$

Three Lagrange interpolated weighted averages were calculated, but the third was dropped from the model, which has the effect of forcing the effect of the lag structure at the final lagged value to zero.

Results: Price Estimation

On the whole, the coefficient estimates for the price estimation model tend to be slightly more erratic than that of the load estimation model. This likely has to do with the introduction of the model-predicted loads into the price model. The coefficients in the price model tend to display the erratic behavior that was present at the hours of 6:00AM and 7:00AM in the load model. Additionally, the same problem that existed at those hours in the load model is present for two different hours in the price model.

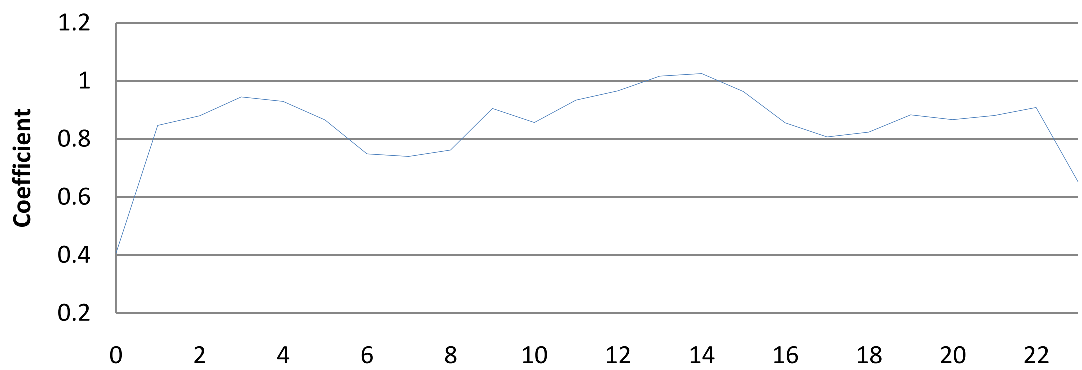

Figure 10: One Hour Lagged Electricity Price

The one-hour lagged electricity price coefficients shown in Figure 10 again reach a value greater than one during two hours, 1:00PM and 2:00PM. To further analyze this, a combination of the one-hour and one-day lagged price coefficients were calculated (just as in Figure 6 for loads). The result was exactly the same as it was in the load estimation: a graph that looks nearly identical to that of the one-hour lagged prices, and combined coefficient estimates greater than one at the same hour. Although this is the same problem that occurred in the load estimation, it appears to be less severe, as the coefficient estimates at these hours tend to be less anomalous than the estimates at 6:00AM and 7:00AM, even in the price estimation models.

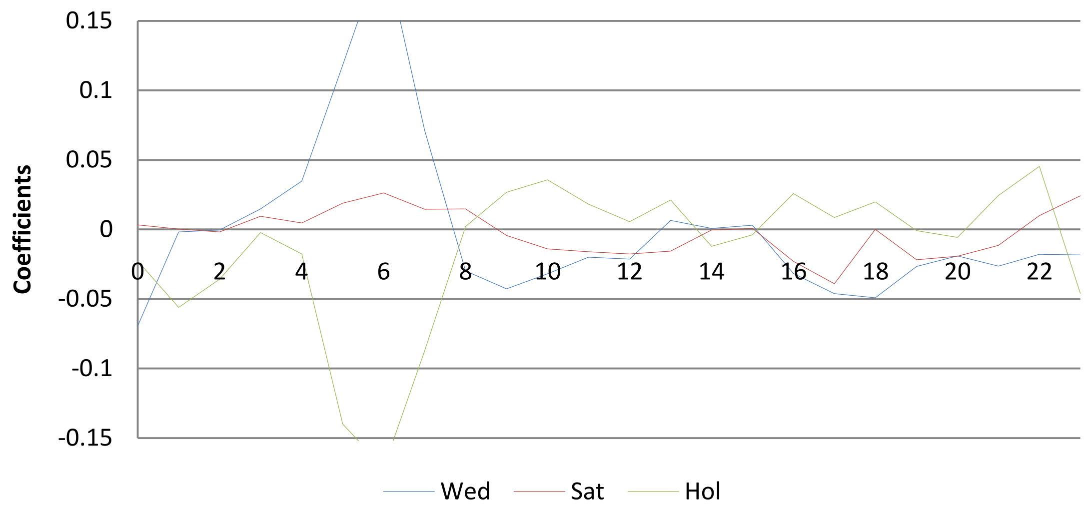

Figure 11: Wednesday, Saturday, and Holiday Coefficient Estimates (Price Estimation)

Figure 11 shows the day-of-the-week and holiday coefficient estimates in the price estimation model. The estimates shown here look very similar to those for the load estimation model, though slightly more erratic. For example, in the weekday variables many of the estimates in the mid-day hours are negative, which is not to be expected. Exactly the opposite is true for the holiday variable, which has positive coefficients during many of the mid-day hours where one would expect them to be negative. An interesting note is that the mid-day hours where these variables behave as expected are the same hours in which the one-hour lagged price coefficient was greater than one. Next, the variables unique to the price estimation model are analyzed.

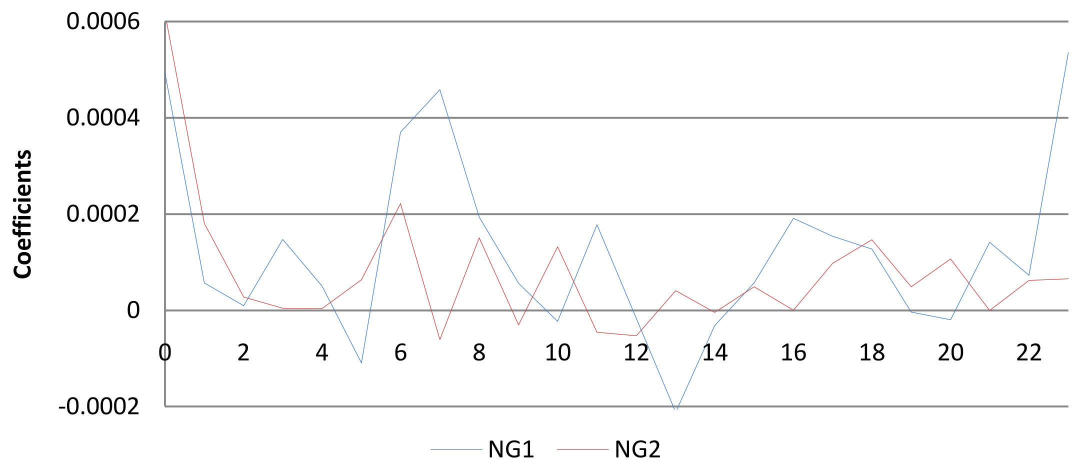

Figure 12: NG1 and NG2 Coefficient Estimates

The coefficient estimates for the natural gas price variables are fairly erratic, though they are positive during most hours, which is to be expected. While the other variables in this model tend to be statistically significant during most hours, the natural gas price variables show less significance. The z-statistics for these variables were measured as greater than two during only three hours for each variable. Referring to Figure 12, those hours occur when the coefficient estimates spike in the positive direction. The hours that are negative or near zero tend to show very little statistical significance (Hour 13 for NG1 excluded). Despite the relatively low significance for these variables, it is very important to keep them in the model, as the price of natural gas is an extremely important factor in determining the price of electricity. The last set of variables in the price model that will be analyzed here are the load variables. Because both linear and quadratic versions of these variables were used, the net effect of a combination of the two variables will be presented instead of the coefficients of each variable on their own.

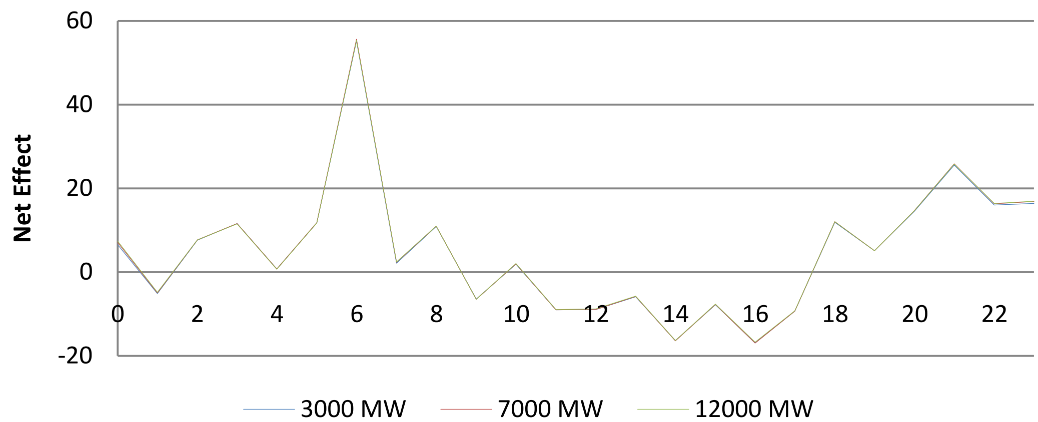

Figure 13: Net Effect of Electricity Load on Price

Figure 13 shows the effect that electricity load has on price at loads of 3000MW, 7000MW, and 12000 MW. In this case, it is not necessarily the actual value of the effect on price that is important, but the difference between the values at different loads. The fact that the effect on price is nearly identical for these three load levels suggests that there is a relatively weak effect of electricity load on price. Figure 13 is somewhat misleading because of the scale of the graph; recall that this effect is being applied to the natural log of electricity price, so that the difference between the load effects only has to be very small to have a substantial effect on the price of electricity. There is indeed a noticeable effect of electricity load on price during individual hours, though the effect is slightly weaker than expected. The variables that are found to be most important are the lagged electricity price variables, such that a change in load that is sustained over several hours will have a much greater effect on price than a change in load during a single hour.

In the end, it was found that the price prediction model has slightly less predictive power than the load prediction model, but averaged throughout a year, the predicted price is still very close to the actual price. In absolute value, the average difference was found to be approximately 11.07% between the actual and predicted prices, but with positive and negative differences cancelling out throughout the year, the average difference was found to be only 0.36%.

CHAPTER 3

High Penetration Scenarios and the Impact of Plug-In Hybrid Electric Vehicles and Vehicle-to-Grid Technology on Electricity Loads and Prices in New York City

With higher levels of participation in a V2G program, there is potential to offset more peaking load or to provide a higher levels of regulation capacity, which is of course the goal of such a program. The problem with high levels of participation, however, is that a decrease in the revenues to the individual participants is expected. This is true for either of the single-use V2G programs that have been discussed, and is thus true for the dual-use program that has been proposed. The first of these to be discussed is the case of V2G for peak reduction.

In the energy market, high levels of PHEV penetration will mean significantly increased load during charging periods, which will translate into increased prices and thus increased charging costs. Additionally, high levels of V2G participation will mean significantly reduced load during peak hours, and decreased loads translate into decreased prices as well. Higher prices during charging and lower prices during vehicle-to-grid discharging translate into decreased profits from the energy market.

In order to estimate the effect of high penetrations of Plug-In Hybrid Electric Vehicles and high participation in a V2G program for peak reduction, the econometric model described in Chapter II is used along with load profiles for all 366 days (leap year) of 2008 that have been adjusted to represent the effect of increased use of PHEVs and V2G.

Load Adjustments

The load adjustments employed here are based upon the figures presented in Table 1 and the estimate of 1,130,002 commuters into New York City on a daily basis (Sadik-Khan, 2007). For the different penetration rates that are used, it is assumed that these rates apply to each driver group equally, such that at a 10% PHEV penetration rate, 10% of the drivers who exist within each group drive a PHEV. To estimate the effect of PHEV charging on load, a regulated charging pattern is assumed, such that charging only takes place between 12:00AM and 6:00AM, which are the hours with the lowest electricity load (and highest vehicle availability). Additionally, the charge rate during these six hours is assumed to be constant.

To estimate the change in load due to peak reduction supplied by V2G, it is necessary to use a V2G participation rate that is a part of the PHEV penetration rate. For example, if the PHEV penetration rate is 50%, and the V2G participation rate is 50%, this implies that 25% of all vehicles are PHEVs that participate in the V2G program. It is assumed that the peak reduction always takes place during the hour that typically has the highest electricity load during weekdays in the summertime (4:00PM). This criterion is used because these are the days that would be most obviously targeted for peak reduction. The hour with the highest electricity load throughout the year is 5:00PM. This difference in the hour of discharge only occurs in the cases with relatively low V2G participation, where peak reduction only takes place during a single hour. With higher rates of V2G participation, the peak reduction is spread over several hours that typically have the highest electricity load. In the case where peak reduction is spread over two hours, the reduction occurs during both 4:00PM and 5:00PM. Beyond the two hour reduction case, the additional hours of peak reduction typically occur before 4:00PM, since the average electricity load drops fairly dramatically after 5:00PM. Only in cases with extremely high penetration rates is the peak reduction spread over enough hours to include hours after 5:00PM. Many of the hours during which the average electricity load is highest are commuting hours; for that reason, the amount of peak reduction that would occur at any hour is multiplied by the vehicle availability percentage at that hour. Figure 14 shows the changes to the average electricity loads in 2008 that are experienced by adjusting the daily load profiles to reflect the load conditions with various combinations of PHEV penetration and V2G participation.

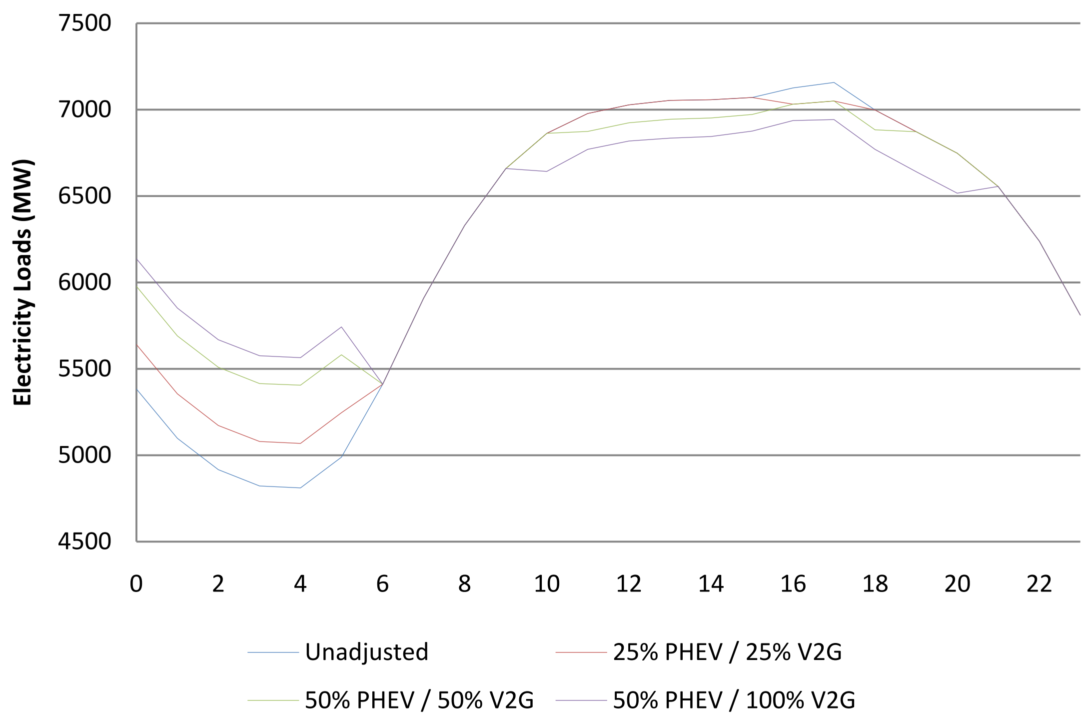

Figure 14: 2008 Adjusted Average Electricity Loads (NYC)

Notice in Figure 14 that the charging load in the 50% PHEV / 50% V2G case is lower than that of the 50% PHEV / 100% V2G case. This is because the spare battery charge that is sold back to the grid during peak reduction needs to be charged as well, which means that increased V2G participation translates into additional charging in addition to the peak reduction that is taking place. The next step in the analysis is to convert the changes in electricity loads into changes in electricity prices.

Price Adjustments and Energy Market Profits

The coefficient estimates from Chapter II are used along with the adjusted loads to create adjusted hourly estimates of the LBMP in New York City in 2008. The same data that was used to estimate the econometric model is used here, and at each hour the value of each variable is set to its actual value at that time period. The exceptions to this are the electricity load variables, which are adjusted according to the penetration rate of PHEVs and the V2G participation rate. Some of the most dominant variables in the model are the lagged electricity prices. Because of this, the electricity prices are affected beyond the hour of changed load. This resulted in a problem of overestimation due to the fact that the charging load at night can be extremely high, and have an effect on the prices for the rest of the day, and even the rest of the year. To remedy this problem, the dynamic price effect is stopped and restarted every day at 7:00AM (after charging has taken place), so that the effect of peak load reduction on prices can be viewed on its own, without the influence of the higher prices at night.

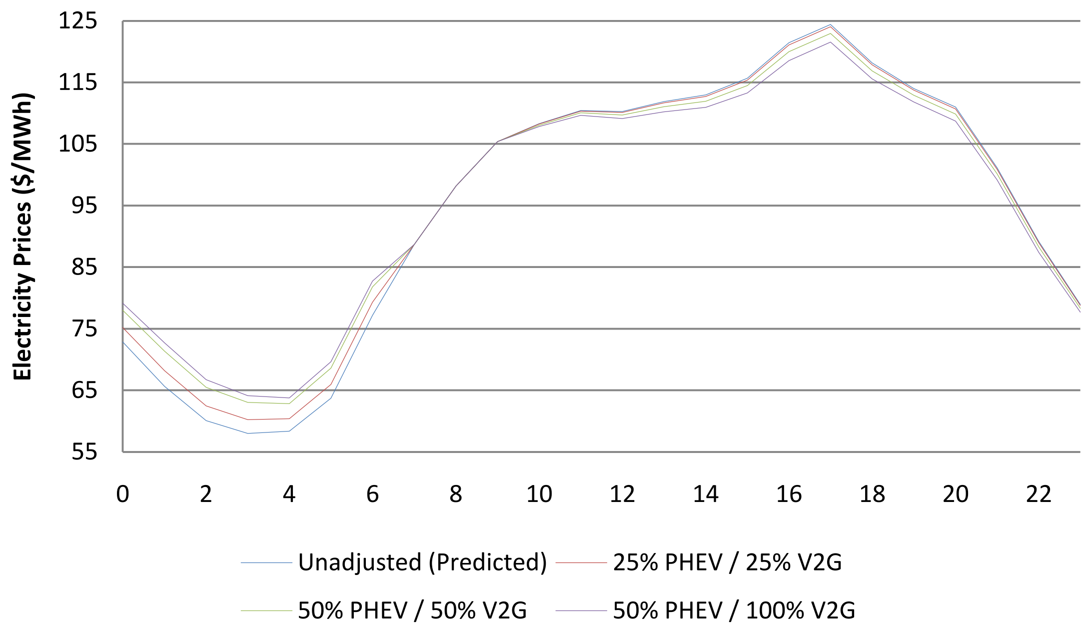

Figure 15: 2008 Adjusted Average Electricity Prices (NYC)

Figure 15 shows the effect of various PHEV penetration and V2G participation scenarios on the New York City LBMP. Using the models estimated here, the change in price at any individual hour is not necessarily on the same scale as the change in load at that hour. Instead, a change in load at a single hour will have an effect on the price for many subsequent hours. Although the price estimation presented here is likely an overestimation of this effect caused by model specification, it is likely that this dynamic price effect does exist to a degree in reality. Because of the relatively weak single-hour effect of load on price, the changes in profits due to higher penetrations of PHEVs and higher participation in V2G are likely slight underestimates.

Table 20: Revenues, Costs, and Energy Arbitrage Profits – Unadjusted Predicted Prices (2008)

Driver Group	Revenues	Costs	Arbitrage Profits
0 – 10	$334	$165	$170
10 – 20	$236	$116	$120
20 – 30	$138	$68	$70
30 – 40	$60	$30	$30

Table 21: Revenues, Costs, and Energy Arbitrage Profits – 25% PHEV / 25% V2G (2008)

Driver Group	Revenues	Costs	Arbitrage Profits
0 – 10	$334	$171	$163
10 – 20	$236	$120	$115
20 – 30	$137	$70	$67
30 – 40	$60	$31	$29

Table 22: Revenues, Costs, and Energy Arbitrage Profits – 50% PHEV / 50% V2G (2008)

Driver Group	Revenues	Costs	Arbitrage Profits
0 – 10	$331	$178	$153
10 – 20	$234	$126	$108
20 – 30	$136	$73	$63
30 – 40	$59	$32	$27

Table 23: Revenues, Costs, and Energy Arbitrage Profits – 50% PHEV / 100% V2G (2008)

Driver Group	Revenues	Costs	Arbitrage Profits
0 – 10	$327	$181	$147
10 – 20	$231	$128	$104
20 – 30	$135	$74	$60
30 – 40	$59	$32	$26

Table 20 shows the energy costs, energy revenues, and energy arbitrage profits using model predicted prices with unadjusted loads. Notice that these (unadjusted price) figures differ from those in Chapter I. This is in part because predicted prices are used instead of actual prices, though the difference between those price measures summed over the year is negligible. The real difference arises because the calculations are slightly different; in the previous section it was assumed that the energy was discharged at the time of day with the maximum LBMP, whereas here it is assumed that energy is sold at 4:00PM in the unadjusted load scenario (this makes the revenue calculations in the adjusted scenarios manageable). Table 21-23 show the energy costs, revenues, and arbitrage profits for various penetration and participation scenarios. In all of the adjusted load cases, the revenues are decreased, the costs are increased, and thus the profits are reduced as compared to the unadjusted scenario.

High Participation and the Capacity Market

In addition to decreased profits from energy arbitrage, participants in a program that uses V2G for peak reduction (or a combined program) would likely see reduced capacity payments with higher rates of participation. The capacity of the aggregated V2G program was defined as the amount of electricity load that can be reduced through the use of the V2G program. With the hourly load data that has been used here, this means that if there is enough V2G capacity that the peak reduction can be spread over more than one hour, then the capacity for each participant in the V2G program will be reduced. If real-time data were used (as might be used in an actual system), then a much smaller increase in the time scale of the peak reduction would result in decreasing marginal capacity.

To give an idea of the magnitude of the reduction in capacity payment in terms of this study, the capacity payment for a V2G participant in the lowest mileage group (0 – 10 miles) was calculated to be $356.19 at 1% participation, where the peak reduction only occurs in only a single hour. In the 50% PHEV penetration and 100% V2G participation scenario, the peak load reduction is spread evenly over 11 hours, implying that the capacity payment to that same individual would be reduced to $32.28. This severe reduction in capacity payment is mostly a symptom of the way the capacity of the V2G program is defined, and the manner in which the adjustments to the peak load were made. In reality, it is unlikely that the load reduction would be spread evenly over several hours, which would mean that the amount of load reduced (in MW) during the hour with the very highest load would probably be greater. Furthermore, there exists no actual definition for the "capacity" of a storage system, which is essential to this type of analysis.

High Participation and Regulation

Along with V2G for peak reduction, there are potential problems with using V2G for regulation in high participation scenarios. The problem lies in the fact that only a certain amount of regulation capacity is needed for the system. In California, the regulation requirements range between 5% and 10% of the load at any given time (CAISO, 2001). If this is applied to the New York City electricity market, which had an average load of 6062MW in 2009, then the amount regulation capacity needed would be on the order of 303MW to 606MW. To fulfill 606MW worth of regulation capacity in the New York Metropolitan Area would require approximately 5.4% participation assuming a 10kW power rating, and 40.2% participation with a 1.33kW power rating. If the amount of regulation capacity provided by the V2G service grows beyond the level that is required, then regulation prices will likely decrease sharply in a competitive market. Alternatively, if prices were controlled, then many regulation-providing generators and V2G participants would be crowded out of the market.

There are reasons to believe that there is more room for regulation-providing V2G participation than the numbers presented above suggest. For example, it is likely the levels of V2G regulation capacity required will be higher than the amount of V2G regulation capacity that is used, in order to ensure reliability; note that this would also have the detrimental effect of reducing the profits to the individual participants. It is suggested in (Quinn, Zimmerle, & Bradley, 2010) that the amount of regulation capacity required would be approximately 2.49 times greater than the amount that would actually be used, which implies that the profits would be scaled back by an equivalent amount. Additionally, the only ancillary service market that we have considered is regulation, but in truth there are other markets (such as the reserves market) in which a V2G service could make a valuable addition; with high rates of participation, the aggregated V2G service could participate in multiple markets. Furthermore, it is likely that there will be significantly increased demand for regulation, reserves, and storage in general due to higher penetrations of intermittent renewable energy sources such as wind and solar.

Conclusions

The results of the economic analysis presented here suggest that there is little financial incentive for PHEV owners to participate in a program that uses V2G technology solely for peak reduction. On the other hand, there is significant potential for financial return for the participants when V2G technology is used for regulation. Though these two (and other) uses for V2G technology are most commonly viewed individually, they are not necessarily mutually exclusive. A program that combines these two uses for V2G technology could provide similar profits for the driver to the V2G-for-regulation case, and additionally provide significant external benefits if it is used for peak reduction on days with extremely high electricity demand and pollution.

With any of the uses for V2G technology that were described here, there exists a tendency for the revenues to decrease and costs to increase as the penetration of PHEVs and the participation in the V2G program increase.

It is likely that these and other problems could be alleviated with a different type of market structure. The analysis conducted here works within framework of the electricity markets that exist today, but perhaps what is actually needed is a completely different type of electricity market, specifically crafted for storage technologies. If this were the case, then the participants in the program could be compensated through a payment mechanism (external to the many payment mechanisms discussed here) and the operators of the grid could determine the optimal use for the stored energy at any particular time. There is some additional evidence of this need in the California energy market, where Western Grid Development L.L.C. requested that its storage devices (batteries) be classified as wholesale transmission facilities and be eligible for rate-based regulation (Wellinghoff, Spitzer, & Norris, 2010). This would most likely be unnecessary if there were a formal market for electricity storage. With a market set up specifically for storage, the storage technologies (V2G included) could provide several services depending on the needs of the grid. These services include peak shifting, regulation, reserves, and even services for which no market currently exists, such as ramping. With this type of storage market, the use of the stored energy could be optimized from the perspective of the grid operator, and with so many different uses for storage, the problem of reduced profits at high penetrations could be alleviated since the effect on any single market would be reduced.

APPENDIX

Load Estimation Coefficients and Z-Statistics

Hour	Cos(1) Coeff	Cos(1) Z	Sin(1) Coeff	Sin(1) Z	Cos(h) Coeff	Cos(h) Z	Sin(h) Coeff	Sin(h) Z	Mon Coeff	Mon Z
0	-0.002	-1.76	-0.00209	-2.87	0.002732	5.08	0.003821	5.75	-0.00656	-6.41
1	0.000149	0.18	-0.00056	-1.05	0.001255	3.15	0.002616	5.93	0.005314	6.68
2	0.001408	2	-0.00011	-0.25	9.74E-05	0.27	0.001071	2.78	0.007077	12.32
3	0.00182	3.42	-4.8E-05	-0.14	-9.2E-05	-0.35	0.000393	1.39	0.010455	24.97
4	0.00168	2.92	-0.00037	-1.03	-7.7E-05	-0.27	0.000289	0.97	0.017516	37.7
5	0.009638	7.71	-0.0009	-0.97	-0.00436	-6.67	0.001046	1.26	0.049829	41.17
6	0.013174	5.86	0.003214	1.97	-0.00345	-2.81	-0.00562	-3.44	0.079788	33.03
7	-0.00524	-2.95	0.005859	4.58	-0.00032	-0.36	-0.00606	-5.31	0.052958	25.12
8	-0.00643	-5.55	0.000216	0.3	-0.00011	-0.2	-0.0013	-2.05	0.017362	13.46
9	-0.00229	-2.75	-0.00069	-1.36	9.48E-05	0.26	-1.7E-05	-0.04	0.003939	3.19
10	-0.00152	-2.06	-0.00112	-2.31	0.000861	2.48	0.001133	2.89	-0.00617	-5.84
11	-0.00112	-1.66	-0.00153	-3.33	0.000577	1.85	0.000756	2.06	-0.00585	-6.02
12	2.22E-05	0.03	-0.00129	-2.93	-1.6E-05	-0.05	0.000472	1.33	-0.00447	-4.64
13	0.000246	0.46	-0.0011	-2.88	-0.00035	-1.2	-0.00025	-0.8	8.35E-05	0.08
14	-0.00029	-0.54	-0.00108	-2.91	0.000372	1.35	2.31E-05	0.08	0.000782	0.86
15	0.002207	3.04	-0.00201	-4.06	0.001584	4.18	-0.00048	-1.27	0.001966	2.03
16	0.009795	10.1	-0.00377	-6.58	0.006308	12.71	-0.00323	-6.71	0.002812	2.22
17	0.019831	17.95	-0.00262	-3.62	0.010579	16.48	-2.1E-05	-0.03	-0.00138	-1.03
18	0.009412	5.87	-0.00107	-1.21	-0.00445	-4.36	0.004069	4.25	-0.01701	-10.48
19	-0.00144	-0.97	-3.2E-05	-0.04	-0.01454	-17.98	0.002367	2.95	-0.01031	-9.31
20	-0.01466	-11.36	0.004575	5.27	-0.00297	-4.14	0.000387	0.47	-0.01073	-9.48
21	-0.01206	-14.27	0.000387	0.69	0.007321	16.59	0.000544	1.15	-0.01209	-16.19
22	-0.00423	-4.44	-0.00154	-2.43	0.004012	8.39	0.002298	4.76	-0.01436	-18.36
23	-0.00326	-3.14	-0.00206	-2.81	0.004212	7.29	0.004075	6.19	-0.01588	-17.27

Load Estimation Coefficients and Z-Statistics

Hour	Tue Coeff	Tue Z	Wed Coeff	Wed Z	Thur Coeff	Thur Z	Fri Coeff	Fri Z	Sat Coeff	Sat Z
0	-0.02128	-18.92	-0.02246	-20.15	-0.02175	-19.56	-0.01958	-18.41	-0.01228	-12.4
1	-0.00059	-0.75	-0.00216	-2.89	-0.00138	-1.83	-0.00114	-1.46	-1.1E-05	-0.01
2	0.004506	6.83	0.004081	6.33	0.004287	7.04	0.003436	4.72	0.001621	2.63
3	0.008935	17.59	0.008182	16.81	0.008539	17.93	0.007646	15.93	0.00208	4.82
4	0.015654	24.98	0.014701	25.88	0.014873	25.38	0.013802	23.74	0.003054	5.57
5	0.052531	33.72	0.051429	33.49	0.051923	32.87	0.049481	31.41	0.009457	6.84
6	0.096069	31.11	0.096013	30.48	0.096905	29.25	0.094505	29.48	0.023122	8.1
7	0.073057	27.11	0.072768	28	0.074219	26.54	0.071513	26.86	0.028991	13.04
8	0.025519	20.47	0.024515	18.85	0.026155	19.27	0.025415	18.82	0.017231	15.12
9	0.005662	5.05	0.005995	6.2	0.005619	5.27	0.006054	6.04	0.007945	10.39
10	-0.0093	-8.3	-0.00852	-8.54	-0.00866	-8.57	-0.00809	-8.1	-0.00124	-1.61
11	-0.00618	-6.05	-0.00586	-6.19	-0.00587	-6.91	-0.00597	-6.65	-0.00413	-5.99
12	-0.00402	-4.24	-0.00302	-3.33	-0.00302	-3.36	-0.00444	-5.18	-0.00572	-8.12
13	0.002118	2.34	0.003229	3.65	0.003274	3.84	0.000239	0.3	-0.00509	-7.3
14	0.002365	3.13	0.003268	4.23	0.003205	4.22	0.000054	0.07	-0.00367	-5.36
15	0.003698	4.25	0.00381	4.51	0.004044	4.55	0.001418	1.63	-0.00243	-3.23
16	0.005181	4.26	0.005311	4.4	0.00448	3.75	0.00113	1.01	-0.00249	-2.98
17	-0.00228	-1.64	-0.00227	-1.69	-0.00484	-3.6	-0.00848	-6.72	-0.00515	-5.33
18	-0.02307	-11.92	-0.02161	-11.79	-0.02383	-13.13	-0.0258	-13.97	-0.00564	-4.36
19	-0.01378	-9.96	-0.01355	-9.75	-0.01491	-10.1	-0.01815	-13.12	-0.00618	-6.2
20	-0.01255	-9.16	-0.01303	-9.8	-0.01457	-10.94	-0.01869	-14.3	-0.01171	-12.26
21	-0.014	-16.31	-0.01421	-16.33	-0.01414	-16.48	-0.01569	-19.2	-0.00557	-7.73
22	-0.01586	-17.52	-0.01493	-17.14	-0.01401	-16.66	-0.00827	-9.31	0.002365	3.06
23	-0.01641	-14.34	-0.01586	-15.75	-0.0136	-13.14	-0.00159	-1.54	0.011372	13.2

Load Estimation Coefficients and Z-Statistics

Hour	Hol Coeff	Hol Z	CDD Coeff	CDD Z	CDDsq Coeff	CDDsq Z	HDD Coeff	HDD Z	HDDsq Coeff	HDDsq Z
0	0.013557	10.78	0.002342	10.67	-4.7E-05	-4.44	4.83E-05	0.4	6.26E-06	2.41
1	0.005479	3.61	0.001214	6.19	-1.5E-05	-1.45	8.04E-05	0.83	4.56E-06	2.05
2	-0.00577	-4.79	0.001014	6.03	-1.5E-05	-1.91	9.14E-05	1.09	2.67E-06	1.42
3	-0.01046	-15.86	0.000565	4.12	-3E-06	-0.43	0.00002	0.31	3.08E-06	2.39
4	-0.01374	-14.51	0.000303	1.9	-5.6E-06	-0.62	0.000103	1.54	5.23E-07	0.4
5	-0.03909	-22.11	0.000548	1.23	-3.4E-05	-1.16	0.000195	1.44	-5.4E-06	-2.28
6	-0.06503	-19.81	-0.00131	-1.6	1.22E-05	0.24	-0.00045	-1.95	-1.1E-06	-0.27
7	-0.05132	-20.06	-0.00252	-5	0.000051	1.79	-0.00038	-1.92	-1.8E-06	-0.5
8	-0.02552	-15.94	0.000449	1.64	-1.7E-06	-0.11	-0.00059	-4.37	8.69E-06	3.06
9	-0.01044	-3.67	0.00168	10.55	-1.5E-05	-1.91	-0.00055	-5.99	1.11E-05	5.63
10	0.002466	1.47	0.001679	12.67	9.18E-07	0.17	-0.00038	-4.65	9.67E-06	5.44
11	0.004831	2.86	0.001434	13.99	1.23E-07	0.03	-0.00024	-2.89	6.22E-06	3.41
12	0.001029	0.58	0.001207	10.99	-2.3E-06	-0.58	-0.00019	-2.26	4.88E-06	2.62
13	-1.3E-05	-0.01	0.000894	9.03	-5.7E-08	-0.02	-0.00017	-2.04	4.39E-06	2.05
14	-0.0001	-0.07	0.000798	8.01	-1.5E-06	-0.45	-8.6E-06	-0.1	8.09E-07	0.38
15	-0.00297	-1.9	0.000618	4.47	3.39E-06	0.7	0.000104	1.25	-1.2E-06	-0.58
16	-0.00275	-1.44	0.000447	2.57	7.84E-06	1.34	0.000515	4.6	-8.8E-06	-3.16
17	0.002175	1.02	0.000156	0.64	2.69E-05	3.06	0.00044	3.62	-4.3E-06	-1.36
18	0.012101	4.5	-0.00021	-0.73	4.76E-05	4.13	0.000131	0.79	9.34E-06	2.41
19	0.009661	3.79	0.000781	3.15	1.43E-05	1.33	0.000436	2.76	-2.2E-06	-0.61
20	0.012457	5.89	0.001332	6.23	2.85E-06	0.3	-6E-05	-0.47	7.18E-06	2.21
21	0.010964	7.14	0.00202	13.46	-1.2E-05	-1.9	0.00021	2.07	1.52E-06	0.6
22	0.010721	7.7	0.00196	10.04	-1.8E-05	-2.1	5.51E-05	0.47	5.6E-06	2.14
23	0.006747	4.46	0.002273	10.03	-4E-05	-3.9	-7.1E-05	-0.6	9.32E-06	4.07

Load Estimation Coefficients and Z-Statistics

Hour	HourLag Coeff	HourLag Z	DayLag Coeff	DayLag Z	Cons	Cons Z
0	0.937767	120.01	0.024082	4.72	0.261832	4.85
1	0.963618	134.58	0.010909	2.74	0.158988	3.84
2	0.965634	159.29	0.010307	2.92	0.161531	4.7
3	0.974152	215.3	0.001818	0.64	0.175924	6.96
4	0.988861	206.55	-0.008	-2.59	0.146702	5.86
5	0.977244	92.12	-0.01714	-2.17	0.336507	5.78
6	1.017285	70.84	-0.0517	-4.45	0.318137	2.93
7	1.077478	153.18	-0.06295	-9.41	-0.07484	-1.08
8	0.979498	260.66	-0.03032	-7.8	0.495366	12.9
9	0.951037	259.59	-0.01611	-5.07	0.614295	19.84
10	0.934568	280	0.000361	0.11	0.603038	20.92
11	0.949449	283.01	-0.00323	-1.06	0.490116	18.36
12	0.968753	269.55	-0.00878	-2.91	0.358812	12.81
13	0.988295	251.32	-0.01426	-5.12	0.227537	8.69
14	0.990409	281.33	-0.01184	-4.46	0.184013	7.6
15	0.988985	251.17	-0.01065	-3.16	0.186736	6.3
16	0.982347	210.15	-0.01284	-3.51	0.26934	7.27
17	0.94374	165.21	0.002199	0.49	0.480826	10.18
18	0.906868	135.62	0.031383	4.43	0.537342	8.28
19	0.914552	156.87	0.018427	3.37	0.578211	11.23
20	0.898062	141.14	0.016632	3.21	0.739861	13.7
21	0.91834	195.2	0.021765	5.4	0.498532	17.12
22	0.923198	181.18	0.02787	6.59	0.381585	11.68
23	0.925161	127.3	0.03131	5.88	0.309769	6.56

Price Estimation Coefficients and Z-Statistics

Hour	Cos(1) Coeff	Cos(1) Z	Sin(1) Coeff	Sin(1) Z	Cos(h) Coeff	Cos(h) Z	Sin(h) Coeff	Sin(h) Z	Mon Coeff	Mon Z
0	0.077504	5.84	0.026948	1.96	-0.00754	-0.67	-0.00668	-0.52	-0.04985	-3.99
1	0.056635	4.86	0.044074	3.69	-0.01105	-1.21	-0.01405	-1.46	0.012628	1.34
2	0.021905	1.53	0.022224	1.59	0.007941	0.68	0.002181	0.19	0.005349	0.79
3	0.030187	4.51	-0.00776	-1.18	-0.00816	-1.68	0.001953	0.38	0.025884	4.5
4	-0.00161	-0.42	0.009467	2.95	-0.00289	-0.95	0.001604	0.49	0.030927	5.45
5	0.043869	3.12	0.013093	1.02	-0.04122	-3.67	-0.01419	-1.22	0.12292	14.96
6	0.097713	7.57	0.013081	1	-0.06051	-5.23	-0.03311	-2.78	0.202116	15.41
7	-0.03114	-2.08	0.062727	4.07	0.031922	2.54	-0.02165	-1.63	0.11692	8.03
8	-0.02812	-4.33	0.018924	2.92	0.00648	1.3	-0.00168	-0.31	0.013991	1.24
9	-0.01753	-3.18	0.002899	0.56	-0.00331	-0.82	0.007355	1.72	-0.01316	-1.26
10	-0.01123	-3.34	0.004518	1.44	0.009066	3.51	0.001463	0.57	-0.02296	-3.02
11	-0.02696	-4.87	-0.00344	-0.62	0.006018	1.38	-0.00425	-0.97	-0.01855	-2.76
12	-0.03107	-8.12	-0.00857	-2.46	0.002107	0.84	-0.00109	-0.39	-0.01464	-2.09
13	-0.03316	-7.01	-0.01446	-3.14	0.00249	0.71	-0.00349	-0.89	-0.0005	-0.09
14	-0.02906	-6.09	-0.01114	-2.59	0.005058	1.53	0.012644	3.25	0.003653	0.57
15	-0.00558	-1.06	-0.01293	-2.51	0.012915	3.21	0.003228	0.73	0.01354	1.95
16	0.063437	13.69	0.00103	0.22	0.037243	9.44	-0.02326	-6.05	-0.02513	-2.22
17	0.11312	15.7	0.035849	4.67	0.038551	5.68	0.006812	1.08	-0.0253	-3.23
18	0.061174	5.93	0.030686	3.19	-0.04365	-4.88	0.001129	0.12	-0.02867	-3.86
19	-0.01549	-1.53	0.010209	0.96	-0.04829	-5.58	-0.01779	-1.81	-0.01536	-2.63
20	-0.06402	-3.49	0.050919	3.05	0.001077	0.07	-0.00877	-0.66	-0.02133	-3.17
21	-0.02262	-2.55	-0.00264	-0.36	0.02163	3.25	0.005169	0.73	-0.02354	-3.82
22	0.019905	2	-0.01961	-2.21	0.007201	0.9	0.000331	0.04	-0.01489	-1.72
23	0.042763	3.44	0.00387	0.34	-0.01726	-1.71	-0.00271	-0.24	-0.01433	-1.29

Price Estimation Coefficients and Z-Statistics

Hour	Tue Coeff	Tue Z	Wed Coeff	Wed Z	Thur Coeff	Thur Z	Fri Coeff	Fri Z	Sat Coeff	Sat Z
0	-0.0669	-4.77	-0.06934	-5.42	-0.06347	-4.97	-0.05358	-4	0.003158	0.27
1	0.012666	1.43	-0.0018	-0.21	0.002738	0.29	0.009807	1.08	0.000175	0.02
2	0.008311	1.16	-0.00053	-0.07	0.007259	0.98	3.24E-03	0.44	-0.00186	-0.29
3	0.01886	3.38	0.014709	2.85	0.021438	4.35	0.010718	2.16	0.009485	1.88
4	0.040068	6.36	0.034633	5.51	0.035483	5.72	0.031527	4.98	0.004505	0.77
5	0.114912	12.38	0.118236	13.14	0.121847	13.64	0.123117	13.58	0.018854	2.2
6	0.193279	13.82	0.202871	14.25	0.197608	14.03	0.183347	13.29	0.026266	2.42
7	0.075302	5.09	0.071319	5.04	0.073073	5.39	0.084465	6.12	0.014529	1.28
8	-0.02211	-1.99	-0.02993	-2.78	-0.03329	-3.01	-0.02293	-2.07	0.014643	1.87
9	-0.03225	-3.37	-0.04278	-4.32	-0.03537	-3.63	-0.03653	-3.7	-0.00434	-0.64
10	-0.04452	-5.91	-0.03191	-4.46	-0.04604	-5.98	-0.03918	-5.22	-0.01392	-2.91
11	-0.02115	-3.22	-0.02007	-3.27	-0.02258	-3.5	-0.01898	-2.94	-0.01619	-3.69
12	-0.02619	-3.74	-0.02132	-2.97	-0.02022	-2.9	-0.02398	-3.49	-0.01775	-3.73
13	-0.00052	-0.09	0.006447	1.1	0.002084	0.35	-0.00201	-0.35	-0.01554	-3.44
14	0.006041	0.95	0.000766	0.12	0.003266	0.52	0.00451	0.72	-0.00034	-0.07
15	0.011767	1.73	0.003074	0.47	-1.8E-05	0	-6.4E-05	-0.01	0.000797	0.15
16	-0.03168	-2.76	-0.03179	-3.08	-0.03529	-3.22	-0.05207	-4.85	-0.02297	-3.46
17	-0.03707	-4.09	-0.04609	-5.26	-0.0432	-4.63	-0.04505	-5.29	-0.03897	-6.13
18	-0.04836	-5.99	-0.04909	-6.29	-0.04383	-5.57	-0.04973	-6.74	-9.2E-06	0
19	-0.02539	-4.6	-0.02654	-4.75	-0.02462	-4.02	-2.87E-02	-5.13	-0.02181	-4.59
20	-0.0197	-2.64	-0.01911	-2.59	-0.02442	-3.27	-0.02275	-3.7	-0.01932	-3.76
21	-0.03019	-4.3	-0.02649	-3.76	-0.0295	-3.97	-0.02763	-4.27	-0.01141	-1.9
22	-0.01931	-2.22	-0.01797	-1.98	-0.01722	-1.79	-0.00943	-1.13	0.009999	1.36
23	-0.01831	-1.58	-0.01848	-1.63	-0.00104	-0.09	0.012065	1	0.02413	2.15

Price Estimation Coefficients and Z-Statistics

Hour	Hol Coeff	Hol Z	NG1 Coeff	NG1 Z	NG2 Coeff	NG2 Z	Load Coeff	Load Z	Loadsq Coeff	Loadsq Z
0	-0.02273	-0.87	0.000493	2.3	0.000618	4.4	0.995665	0.19	-0.0226	-0.08
1	-0.05614	-2.81	5.66E-05	0.29	0.00018	1.88	-1.33489	-0.49	0.086845	0.55
2	-0.03576	-1.63	9.77E-06	0.08	2.73E-05	0.47	1.743977	0.87	-0.09904	-0.85
3	-0.00228	-0.27	0.000147	1.31	4.56E-06	0.08	2.732301	1.91	-0.16104	-1.93
4	-0.01777	-2.02	5.03E-05	0.51	3.69E-06	0.07	0.23555	0.16	-0.01749	-0.2
5	-0.14005	-10.79	-0.00011	-0.6	6.35E-05	0.66	2.696072	1.07	-0.15423	-1.05
6	-0.17155	-7.41	0.00037	1.76	0.000222	1.94	12.6738	5.48	-0.72204	-5.43
7	-0.08738	-3.7	0.000458	1.89	-6.1E-05	-0.52	0.274716	0.16	-0.00175	-0.02
8	0.002102	0.14	0.000194	0.87	0.000151	1.49	2.423996	1.9	-0.1336	-1.84
9	0.026697	1.59	5.61E-05	0.34	-3.1E-05	-0.41	-1.44121	-1.17	0.079672	1.14
10	0.035573	2.92	-2.3E-05	-0.29	0.000132	3.49	0.320917	0.36	-0.01118	-0.23
11	0.018194	2.11	0.000178	1.38	-4.6E-05	-0.75	-2.1577	-3.1	0.127871	3.3
12	0.005483	0.33	-1.7E-05	-0.15	-5.3E-05	-1.08	-2.1335	-2.26	0.12691	2.4
13	0.021142	2.38	-0.00021	-2.46	4.07E-05	0.93	-1.47845	-2.14	0.09239	2.4
14	-0.01215	-1.04	-3.1E-05	-0.36	-4.5E-06	-0.11	-3.79139	-4.99	0.217974	5.14
15	-0.00386	-0.34	5.67E-05	0.63	4.88E-05	1.23	-1.88721	-2.25	0.113913	2.42
16	0.025794	1.22	0.000191	1.17	1.93E-07	0	-4.00644	-2.68	0.236319	2.82
17	0.008601	0.5	0.000154	1.56	9.77E-05	1.92	-2.1941	-1.58	0.12818	1.64
18	0.019717	1.52	0.000128	0.93	0.000146	2.18	2.664615	1.89	-0.1475	-1.86
19	-0.0009	-0.05	-3.5E-06	-0.03	4.89E-05	0.86	1.186314	0.74	-0.06909	-0.77
20	-0.00576	-0.28	-2E-05	-0.12	0.000107	1.28	3.243884	1.54	-0.17858	-1.5
21	0.024287	1.04	0.000141	1.11	-5.8E-07	-0.01	5.741009	2.93	-0.31891	-2.89
22	0.045316	1.82	7.26E-05	0.32	6.19E-05	0.61	3.505462	1.12	-0.18781	-1.06
23	-0.04584	-1.7	0.000536	2.53	6.56E-05	0.6	3.434288	0.73	-0.1736	-0.64

Price Estimation Coefficients and Z-Statistics

Hour	HourLag Coeff	Hourlag Z	DayLag Coeff	DayLag Z	Cons	Cons Z
0	0.403381	10.83	0.130635	2.48	-5.3077	-0.24
1	0.846866	38.92	0.09477	4.72	5.112479	0.43
2	0.879589	54.48	0.088033	5.69	-7.63045	-0.88
3	0.944429	80.33	0.041204	3.46	-11.6083	-1.89
4	0.929181	77.74	0.043097	3.41	-0.65868	-0.1
5	0.865624	42.49	0.04326	2.26	-11.4054	-1.05
6	0.748009	34.5	0.026435	1.13	-54.7976	-5.45
7	0.739454	34.93	0.085253	3.95	-1.53816	-0.2
8	0.761492	48.28	0.088808	5.07	-10.3257	-1.86
9	0.905167	61.12	0.062507	3.93	6.753045	1.25
10	0.856634	70.72	0.048919	4.33	-1.53088	-0.39
11	0.933603	83.22	0.025948	2.11	9.279135	2.97
12	0.965925	80.89	0.025395	1.98	9.021348	2.15
13	1.016813	83.57	-0.0102	-0.96	5.850113	1.89
14	1.025189	92.21	0.002493	0.25	16.34976	4.8
15	0.963205	82.59	-0.00138	-0.13	7.929075	2.12
16	0.855162	59.39	0.060515	4.17	17.3723	2.6
17	0.806399	54.36	0.080459	5.65	9.898811	1.6
18	0.82303	50.51	0.066776	4.23	-11.6041	-1.85
19	0.883222	61.04	0.045589	2.92	-4.77991	-0.67
20	0.866248	53.61	0.013243	0.75	-14.2127	-1.52
21	0.880643	55.59	0.079139	4.87	-25.7307	-2.96
22	0.908739	39.92	0.098409	5.37	-16.4747	-1.2
23	0.652321	28.37	0.173944	5.8	-16.2	-0.78

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